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THREE ESSAYS ON RELATIONSHIPS AMONG FINANCIAL INSTITUTIONS

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DEDICATION

I dedicate this to my parents, siblings, academic adviser and committee members without whom it was almost impossible to complete my dissertation.

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ABSTRACT

This dissertation investigates relationships among financial institutions. I examine relationships from three different perspectives: relationships among affiliated banks and life insurers, correlated trading among life insurers, and relationships between insurers and bond dealers in the over-the-counter markets. The primary purpose of my research is to examine the benefits and drawbacks of relationships among financial institutions. The main findings are as follows. First, life insurers with bank affiliates had higher growth rates relative to other life insurers during the 2008 financial crisis. However, these Bank-Life Financial Holding Companies performed worse than Non-Bank-Life Financial Holding Companies during the same period. It indicates that the cross-selling effect is not large enough to increase firm's performance. Second, U.S. life insurers' investment decisions in corporate bonds are correlated across companies. However, the evidence in this dissertation is mixed as to whether insurers' investment behavior has the potential to disrupt financial markets. Little evidence shows that this herding pushes prices away from fundamental values. Third, we find that there is variation in the impact of trading relationships on execution costs. The variation is related to the variation in a customer's market power in the dealer relationship. In addition, the outsourcing of investment services to an affiliate of a dealer help customers with the weak market power to decrease bond execution costs. These findings of three essays add to the financial institution and relationship literature.

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CHAPTER 1

INTRODUCTION

This dissertation is composed of three essays on relationships among financial institutions. I examine relationships from different perspectives: relationships among affiliated banks and life insurers, correlated trading among life insurers, and relationships between insurers and bond dealers in the over-the-counter markets.

The first essay in Chapter 2 analyzes whether bank affiliate relationships affect life insurers' growth rates, excess return on asset, and scope economies. I find that life insurers with bank affiliates had higher growth rates relative to other life insurers during the 2008 financial crisis. The higher growth is derived mainly from annuity products (deposit-type insurance products), which are often viewed as substitutes for bank Certificates of Deposit (CD). In addition, return on assets before claim payments, operating cost scope economies, and revenue scope economies all improved during the same period. Meanwhile, return on assets after claim payments, claim cost scope economies and profit scope economies deteriorated. This growth effect is consistent with cross-selling between banks and life insurers. However, the cross-selling effect was not sufficiently large to cover the underwriting loss. Overall, my results suggest that the Bank-Life Financial Holding Companies performed worse than Non-Bank-Life Financial Holding Companies during the 2008 financial crisis.

The second essay (co-authored with Greg Niehaus) in Chapter 3 studies the impacts of correlated trading among life insurers on bond prices. Our evidence indicates that U.S. life insurers' investment decisions in corporate bonds are correlated across companies within the life insurance industry. On average, sell-side herding is greater in smaller bonds, bonds with lower ratings, and bonds that have been downgraded. Moreover, herding is more pronounced when insurers that are part of a group that has been designated as a SIFI trade the bond. Sell-side herding tends to follow negative abnormal returns. Also, bond returns are abnormally low during the quarter when insurers exhibit high sell side herding. However, we do not find that these price effects are subsequently reversed, which is what one would expect if the selling pressure pushed prices away from fundamental values.

The third essay (co-authored with Greg Niehaus) in Chapter 4 examines the impacts of relationships between customers and dealers on bond execution costs, where a relationship is defined to exist if the customer and dealer traded in the previous quarter. Unlike Di Maggio et al. (2017), we find that previous trading with a dealer is associated with higher execution costs for the customer, on average. Further investigation reveals that there is variation in the impact of trading relationships on execution costs and that the variation is explained by variation in a customer's market power in the dealer relationship. In addition, the outsourcing of investment services to an affiliate of a dealer improves bond execution costs for customers with weak market power when they trade with a relationship dealer.

Chapter 5 summarizes the findings of Chapters 2, 3, and 4 and discusses the implications of these results to financial institutions and regulators.

CHAPTER 2

DOES AN AFFILIATED BANK IMPROVE LIFE INSURER PERFORMANCE DURING THE 2008 FINANCIAL CRISIS?[1]

2.1 Introduction

Diversification creates several internal markets among different types of entities, such as internal capital markets, internal labor markets, and internal sales channels (Berger, Demsetz and Strahan, 1999; Laeven and Levine, 2007; Tate and Yang, 2015). Different theories suggest conflicting predictions regarding the impact of internal markets on firm performance. Stein (1997) and Maksimovic and Phillips (2002) assume that top managers have access to better information, which allows them to allocate resources based on the relative profitability of growth opportunities and to increase firm value as a result. On the other hand, Scharfstein and Stein (2000) argue that agency problems cause top managers to misallocate resources. Thus, firm value might be jeopardized when stronger divisions subsidize weaker divisions, leading to so-called "socialism" in internal capital allocation. The empirical evidence from the literature is mixed.[2] However, diversification discounts and the drawbacks of cross-subsidization by internal capital markets are frequently highlighted in the financial industry literature (Campello, 2002; Stiroh and Rumble, 2006; Laeven and Levine, 2007; Holod and Peek, 2010).

[1] Chia-Chun Chiang. To be submitted to Journal of Risk and Insurance.
[2] Kuppuswamy and Villalonga (2015) support the efficiencies of internal capital markets. However, other studies find evidence of inefficiencies (Glaser, Lopez-De-Silanes, and Sautner, 2013; Duchin and Sosyura, 2013).

The purpose of this paper is to provide new evidence on internal markets and scope economies in financial companies. I investigate whether life insurers with bank affiliates grow faster relative to life insurers without bank affiliates during the 2008 financial crisis. Furthermore, I examine whether the scope economies of Bank-Life financial holding companies (BLFHCs) changed during the 2008 financial crisis. I define a BLFHC as a holding company that includes a life insurance company and a bank. I find that BLFHC life insurers enjoyed higher premium growth rates relative to non-BLFHC life insurers during the financial crisis. I also find that BLFHCs enjoyed greater excess ROA before claim payments, operating cost scope economies and revenue scope economies during the 2008 financial crisis than during normal times. In contrast, excess ROA after claim payments, underwriting cost scope economies and profit scope economies worsened during the same period.

The Gramm-Leach-Bliley Act of 1999 (GLBA) allowed U.S. financial conglomerates to engage in both banking and insurance under one roof, similar to universal banks in Europe (Carow, 2000; Morrison, 2015).[3] However, regulators from both the banking and insurance industries have remained concerned about the potential negative effects involved in combining banking and insurance, particularly those effects related to cross-subsidization, which might drag down the financial health of the other financial entities in a group. Consequently, although regulations allow combinations, resource transfers are constrained within financial conglomerates by restrictions on internal

[3] Prior to 1999, national banks could sell insurance products only under certain specific situations under the National Banking Act of 1918. However, banks were prohibited from underwriting insurance contracts based on the Bank Holding Company (BHC) Act of 1956. The Citicorp-Travelers group merger in 1998 is often understood as the catalyst for the GLBA (Carow 2000).

transactions, such as firewalls (Houston, James and Marcus 1997; Omarova 2011; Koijen and Yogo 2015).[4]

To identify the internal market activities between banks and life insurance companies, I examine U.S. life insurers' growth rates from 2004 to 2011. In particular, I focus on the 2008 financial crisis because it is the first banking-related financial crisis following passage of the GLBA. Moreover, although internal market functions are expected to be most valuable in a turbulent market, regulators' concerns – such as those involving over-subsidization among financial groups – are also likely to be heightened during a financial crisis (Kuppuswamy and Villalonga, 2015; Harrington, 2009).

I hypothesize as follows: If internal markets transfer resources to units in need in a financial crisis, then BLFHC life insurers should experience higher growth rates than non-BLFHC insurers during a financial crisis relative to non-crisis periods. Banks with excess funding from potential depositors can transfer these potential depositors to their affiliated life insurers that sell fixed annuity products, which are typically viewed as substitutes for bank certificates of deposit (CDs). Affiliated life insurers suffering operating and investment losses can thus obtain funding to maintain their risk-based capital ratios. I focus on cross-selling, an internal transfer channel that has received little attention in the academic literature.[5] According to a 2009 LIMRA report, the bank sales channel had the second highest total annuity market share with fixed annuity sales improving 94% in 2008. [6] Given that banks and insurers offer products that are close substitutes, e.g., bank CDs and

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[4] With regard to banking regulation, section 23A of the Federal Reserve Act limits the extent to which a bank or its subsidiaries can engage in lending with and/or purchasing equity or assets from any affiliate. With regard to insurance regulation, many states also set restrictions on non-insurance subsidiary investments.
[5] Previous studies focus on the impacts of cross-selling on firm value but do not discuss how cross-selling helps during a financial crisis.
[6] LIMARA is a worldwide research organization that provides insight and analysis on retirement, insurance and distribution. The related article is titled "FA Sales Skyrocketed In '08 While VA Sales Plunged: LIMRA".

fixed annuities, banks can transfer customers to their affiliated life insurers.[7] By contrast, non-BLFHC life insurers must pay higher costs (such as higher commissions) to sell products through non-affiliated banks (external markets). In other words, cross-selling might be an efficient means of transferring resources.

To investigate whether an internal bank channel helped the growth of life insurers during the 2008 financial crisis, I use company-level data from the National Association of Insurance Commissioners (NAIC), representing 460 life insurers from 261 financial conglomerates over the 2004-2011 period. I find that BLFHC life insurers enjoyed greater growth rates relative to non-BLFHC insurers during the financial crisis compared to non-crisis periods even after controlling for other potential internal capital transfer channels (such as capital transfers and reinsurance change).

A key concern for any analysis of the effects of internal markets is the endogeneity of BLFHC formation. In particular, life insurance growth may induce conglomerates to incorporate both banks and life insurers, i.e. the causality is reversed. In light of this issue, I use three econometric techniques in the analysis of my BLFHC internal markets results. First, I lag all the financial variables because lagged financial variables and current growth are less likely to be jointly determined (Berger and Bouwman, 2013). Second, I incorporate group fixed effects into the regression models to control for a wide range of group-specific characteristics (outside of BLFHCs) that might be driving the results (Laeven and Levine, 2007; Cremers, Huang and Sautner, 2011). Third, I employ propensity score matching for BLFHC and non-BLFHC life insurers based on firm fundamentals to allow for various

[7] See Waggoner, J. (2011, December 13). What to ask before you buy an annuity; Fixed rate or variable? What are the costs? USA TODAY. Retrieved from FACTIVA.

functional forms of the relation between insurer characteristics and revenue growth (Duchin and Sosyura, 2014).

If the marginal return on added capital in life insurers is greater than a bank in the group, then transferring resources from banks to insurance companies is good for the entire conglomerate because it improves resource reallocation, which increases conglomerate value (Stein, 1997; Maksimovic and Phillips, 2002; Niehaus, 2017). However, if the opposite situation holds, then transferring resources is likely to reduce conglomerate value. Previous studies show that inefficient transfers may happen as the result of agency problems. Managers' rent-seeking behavior and the portion of manager ownership can result in agency problems and inefficient transfers (Scharfstein and Stein, 2000; Ozbas and Scharfstein, 2010; and Glaser, Lopez-De-Silanes, and Sautner, 2013).

To examine the performance of BLFHCs, I compare excess ROA and scope economies during the financial crisis to those of non-crisis times. I use bank data from the Research Information System (RIS) database of the Federal Deposit Insurance Corporation (FDIC) and follow similar methodologies to those employed by Laeven and Levine (2007), Berger and Mester (1997), Berger, Cummins, Weiss and Zi (2000), Cummins and Weiss (2013), and Yuan and Phillips (2008). In this manner, I find that BLFHCs enjoyed greater excess ROA before claim payments, operating cost scope economies and revenue scope economies during the 2008 financial crisis than during normal times. However, excess ROA after claim payments, underwriting cost scope economies and profit scope economies worsened. These results are consistent with the inefficiency hypothesis.

My paper contributes to the literature on internal markets and corporate diversification. Whereas previous studies focus on internal markets in the same financial industry, I examine the operation of internal markets across financial industries through cross-selling during the 2008 financial crisis. My analysis reveals new evidence regarding how BLFHCs' excess ROA and scope economies change with market conditions. The evidence suggests that diversified conglomerates performed worse during the financial crisis, which is not consistent with the results of Kuppuswamy and Villalonga (2015). More importantly, the reason for the poorer performance is from the underwriting loss, which echoes the concerns of selling long-term policies at deep discounts by life insurers (Koijen and Yogo, 2015)

My findings also enhance our understanding of the resource transfer channel. A number of commonly used methods of transferring resources, including capital injection (Powell, Sommer and Eckles, 2008; Holod and Peek, 2010; Cremers, Huang and Sautner, 2011), loan sales (Holod and Peek, 2010), shareholder dividends deduction (Powell, Sommer and Eckles, 2008; Niehaus, 2015) and reinsurance contract usage (Powell, Sommer and Eckles, 2008), have been examined in the literature. However, the role of cross-selling in internal markets is overlooked. BLFHCs are expected to use the cross-selling channel to move their resources because of regulatory constraints.

My paper examines similar issues as those investigated by Kuppuswamy and Villalonga (2015), who aim to determine whether diversification created value during the 2008 financial crisis. Those authors use Compustat segment data to investigate general conglomerate value changes during the financial crisis and also find that the efficiency of internal capital allocation increased significantly during the crisis. My paper differs from theirs in two ways. First, I use regulatory reporting data, and I thus avoid the self-reporting issue in Compustat's segment data. Second, I focus on financial institutions instead of general institutions. The failure of a financial institution due to cross-subsidization during a financial crisis is of great concern to regulators. The finding of this paper is consistent with the hypothesis that customer transfers did occur among BLFHCs during the 2008 financial crisis. However, the effect of cross-selling was not sufficiently large to cover the underwriting loss. My findings are not consistent with Kuppuswamy and Villalonga (2015). BLFHCs perform worse than non-BLFHCs during a financial crisis.

This remainder of this paper is organized as follows. Section 2.2 describes the development of the empirical hypotheses. Section 2.3 contains the data and sample selection processes. Section 2.4 presents the empirical results, while Section 2.5 contains additional evidence and robustness checks. Section 2.6 examines the efficiency of resource transfers, and Section 2.7 concludes.

2.2 Development of Empirical Hypotheses

In this section, I review existing theory and the current empirical literature to formulate my empirical hypotheses regarding resource transfers and changes in scope economies.

2.2.1 Resource Transfers Hypothesis:

Hypothesis 1: During the financial crisis, the growth rates of BLFHC life insurers are higher than those of non-BLFHC life insurers compared to non-crisis periods.

Information problems can create a wedge between internal and external financing (Myers and Majluf, 1984). Internal capital markets are assumed to mitigate asymmetric information problems because headquarters has more information about its subsidiaries than outsiders. Thus, headquarters can shift funds among its subsidiaries and avoid underinvestment problems (Stein, 1997). The function of the internal markets is likely to be more important during financial crises because corporate headquarters adds more value when it reallocates funds across projects in a credit-constrained environment (Kuppuswamy and Villalonga, 2015).

Nonetheless, some previous studies find that headquarters may attempt to shift capital to those subsidiaries within the conglomerates that have a greater need for capital (Holod and Peek, 2010; Cremers, Huang and Sautner, 2011). During the 2008 financial crisis, many life insurers appear to have been financially constrained (Koijen and Yogo, 2015). If internal markets are operational during the same period, life insurers with bank affiliates are expected to obtain resources from affiliates and therefore grow faster than insurers without such affiliates.

Standard resource transfers, including capital injections (Powell, Sommer and Eckles, 2008; Holod and Peek, 2010; Cremers, Huang and Sautner, 2011; Niehaus, 2017), loan sales (Holod and Peek, 2010), shareholder dividends reduction (Powell, Sommer and Eckles, 2008; Niehaus, 2017) and reinsurance contract usage (Powell, Sommer and Eckles, 2008), have been examined in the finance literature. However, the role of cross-selling in internal markets remains overlooked, and I hypothesize that BLFHCs use the cross-selling channel to move their resources and avoid regulatory constraints.

It is important to consider customer transfers for two reasons. First, one of the main benefits of BLFHCs is that the affiliated parties can share customer bases and sell their products to the other client bases (Berger, Cummins, Weiss and Zi, 2000). However, there is limited research on customer transfer channels. Second, there are several regulatory impediments involved in the internal capital markets of BLFHCs (Houston, James and Marcus, 1997; Koijen and Yogo, 2015). BLFHCs face several constraints when seeking to transfer capital to subsidiaries. For example, subsidiary lending and capital transfer are both closely regulated by section 23A of the Federal Reserve Act and the Insurance Holding Company Act (Omarova, 2011; Koijen and Yogo, 2015). By contrast, customer transfers are more flexible because of fewer constraints. Thus, life insurers with bank affiliates are expected to grow faster than those without bank affiliates during the 2008 financial crisis even after controlling for traditional resource transfer channels because of cross-selling effects.

Cross-selling is expected to be particularly useful during financial crises because annuity products issued by life insurers are often understood as substitutes for bank CDs (Scism, 2013). During the 2008 financial crisis, many individuals sought a safe haven in which to keep their cash. The headquarters of BLHCs had the option to allocate these potential customers to either fixed annuities or bank CDs in two different affiliated entities (Waggoner, 2009; Beatrice and Montminy, 2009). Transferring customers from banks to life insurers not only helps the constrained life insurers but also the banks. Life insurers could record their liabilities below their intrinsic values during the financial crisis based on the Standard Valuation Law, such that additional insurance revenues (increasing capital) partially solved the problems of financially constrained life insurers (Koijen and Yogo, 2015). After the crash of the mortgage loan markets, banks also became more conservative about making loans, partly because of increases in loan losses and/or other liquidity issues (Gan, 2007; Santos, 2011). In addition, low loan demand during the financial crisis also made it practically difficult for banks to make more loans. Thus, the headquarters of financial conglomerates were incentivized to transfer customers from banks to life insurers.

Previous studies show that constrained life insurance companies responded during the financial crisis by selling downgraded bonds to avoid higher risk-based capital requirements (Merrill, Nadauld, Stulz and Sherlund, 2014) and by selling bonds with embedded capital gains (Ellul, Jotikasthira, Lundblad and Wang, 2015), seeking government bailouts (Massad, 2012; GAO, 2013; Koijen and Yogo, 2015), raising funds in the external capital markets (Berry-Stolzle, Nini, and Wende, 2014), receiving capital from affiliated entities in their group (Niehaus, 2017), and lowering product prices to sell more policies, all with the aim of reporting higher capital (Koijen and Yogo, 2015). However, the effects of cross-selling by affiliated banks through their internal markets have not yet been investigated. This paper fills this research gap.

2.2.2 Efficiency Hypothesis

Hypothesis 2.a: Resources transferred from its bank affiliates to BLFHC's life insurers add to a BLFHC's scope economies and excess ROA (efficiency hypothesis)

Hypothesis 2.b: Resources transferred from its bank affiliates to BLFHC's life insurers decrease a BLFHC's scope economies and excess ROA (inefficiency hypothesis)

On the one hand, the efficiency hypothesis assumes that top managers make investment decisions to increase conglomerates' values. Thus, they will allocate resources to firms with better investment opportunities (Stein, 1997; Maksimovic and Phillips, 2002). On the other hand, under the inefficiency hypothesis, top managers allocate resources to subsidiaries with worse investments because of agency problems (Scharfstein and Stein, 2000; Ozbas and Scharfstein, 2010; Glaser, Lopez-De-Silanes, and Sautner, 2013). Previous studies show that the evidence on this topic is mixed (Glaser, Lopez-De-Silanes, and Sautner, 2013; Duchin and Sosyura, 2013; Kuppuswamy and Villalonga, 2015).

If resource transfers are found within BLFHCs, then efficient and inefficient resource transfers might simultaneously exist, based on the arguments discussed above. In the case of banks and insurers combined in a conglomerate, banks might be willing to transfer resources to affiliated insurance companies because they might then shift their potential liabilities to the insurers and earn fee income (Stiroh and Rumble, 2006). Moreover, deposit insurance and the too-big-to-fail concerns of authorities increase banks' moral hazard problem (Eisenbeis and Kaufman 2010; Morrison 2010). Insurance companies might thus be willing to accept the transfer because life insurers' manager compensation is linked to insurance revenues, and these transfers increase insurance revenues and thus increase executive compensation as well (Mayers and Smith, 1992). Moreover, statutory reserve regulations, which allow life insurers to record far less than a dollar of reserve per dollar of future insurance liability, further increase incentives to transfer resources to insurance companies (Koijen and Yogo, 2015).

Because of the special transfer channel, we cannot directly measure the impacts of internal banking channel on confluent's performance. Thus, we measure the change in conglomerate's performance. If the conglomerate's performance worsened during the 2008 financial crisis, it indicates that the cross-selling effects are not large enough to improve group's performance. I examine both the changes in excess ROA and scope economies during non-crisis times and the 2008 financial crisis.

2.3 Data and Methodologies

2.3.1 Data

To compare growth for insurers belonging to BLFHCs with those not belonging to BLFHCs, I employ company-level data on premiums and other financial information from the annual statements of the National Association of Insurance Commissioners (NAIC) covering from 2004 to 2011. My initial sample consists of all insurer groups and stand-alone insurers. I first exclude stand-alone insurers (those without other affiliated companies) and reinsurers because stand-alone insurers and reinsurers have very different firm organizations and operations than financial conglomerates. I drop insurer-year observations with negative or zero surplus, total assets, total expenses and new direct premiums. The reason for these deletions is that firms with negative or zero values for these key variables cannot be considered as normal operating entities.[8] Furthermore, I exclude inactive firms. I also delete life insurers that issue no annuity products during the sample period because my hypothesis is based on the assumption that annuities are substitutes for bank CDs. If life insurers do not sell annuity products, banks would have difficulty transferring potential customers to life insurers. Because I use 1-year lagged versions of most variables, I exclude those firm-year observations for which the preceding year of data are unavailable, which results in a sample of 2,757 insurer-year observations for 460 insurers (261 financial conglomerates) from 2004 through 2011.

A life insurer is considered a member of a BLFHC if it is either a subsidiary of a bank holding company or has a bank affiliate(s)[9]. A life insurer is considered a member of a non-BLFHC if it does not have any bank affiliates but has other life insurer affiliates. There are 168 unique BLFHC life insurers (72 BLFHC groups) and 292 non-BLFHC life insurers (189 non-BLFHC groups) in my sample. The data's summary statistics are

[8] Insurance companies are highly regulated and subject to numerous legal requirements. Thus, for insurers that cannot operate normally, insurance commissioners will intervene in their operations. I omit these abnormal firms to exclude the effects of government.

[9] The NAIC requires life insurers to report whether they have bank affiliates in annual reports. In my analysis, non-depository trusts are not considered bank affiliated companies. Non-depository trusts cannot accept deposits from individuals, so they cannot transfer potential depositors to life insurers.

presented in Table 2.1, Panel A. On average, BLFHC life insurers are older companies with greater assets, higher reinsurance amounts, lower state concentration index and higher efficiency. In addition, a higher proportion (29%) of BLFHC life insurers is focused on annuity products, i.e., these insurers derive at least 75% of their premiums from annuity products.

Bank characteristic data are from the Research Information System (RIS) of the FDIC. Summary statistics for the data are presented in Table 2.1, Panel B. On average, BLFHC banks have higher deposit growth rates, take greater risks and are involved in more mergers and acquisitions. BLFHC banks are younger, larger, and more liquid. In addition, BLFHC banks have higher capital ratios.

2.3.2 Methodologies

Following Epermanis and Harrington (2006) and Cole, Fier, Carson and Andrews (2015), I analyze both direct ("written") new premium growth and net new premium growth (direct premiums plus premiums for reinsurance assumed minus premiums ceded to reinsurers). I define premium growth as $\Delta P_t = P_t - P_{t-1}$, where P_t represents log premiums in year t for direct and net premiums and truncated growth at -1 and 1. I separately calculate the growth rate by each line of business and calculate the weighted growth rate based on the proportion of each business to total business premiums. Unlike previous papers, this paper does not use industry-adjusted premium growth because year fixed effects capturing industry-wide effects are already included in the regressions.

The empirical model used to test my first hypothesis is specified for insurer i at time t as follows:

$$y_{it} = \alpha_i + \beta_t + \gamma \text{BLFHC}_{it} + \delta FC \times \text{BLFHCs}_{\,it} + \theta X_{it-1} + \varepsilon_{it},$$

where yit is the premium weighted gross (net) new premium growth rate. The independent variables of interest are BLFHC and FC×BLFHC. BLFHC equals one if an insurer belongs to a BLFHC and zero otherwise. FC is a dummy variable that is equal to one in 2008 and zero otherwise. The interaction term FC×BLFHC equals one if an insurer belonged to a BLFHC in 2008 and zero otherwise. αi represents group fixed effects, and βt represents time fixed effects. I include group fixed effects to control time-invariant group level variables. X_{it-1} is a vector of firm characteristics. If cross-selling helped the growth of life insurers during the financial crisis, then δ should be positive. I estimate the regression model using an ordinary least squares (OLS) method, and I cluster standard errors by financial group to allow for within-group correlation of residuals in premium growth. In addition, I lag financial variables one period (except for M&A, see below for the definition) relative to premium growth to mitigate the potential endogeneity problem.

The control variables include the following firm characteristic control variables and premium-related control variables:

Firm Characteristic Control Variables:

Capital. In theory, financial institutions with more capital enjoy a competitive advantage and thus should be able to earn greater market share (Berger and Bouwman, 2013). Capital represents the insurer's capacity and ability to write additional premiums (Powell, Sommer and Eckles, 2008). More capital is expected to support a larger business. However, Lyandres (2006) proposes that capital and market share can be negatively correlated because firms that are more highly leveraged tend to aggressively expand their market shares. In addition, capital is considered the ratio to measure firm-level risk. Insurers with lower capital ratio have greater desire for risk-taking (Downs and Sommer, 1999; Cummins and Doherty, 2002). Life insurers with higher risk levels might find it more difficult to improve their premium growth because of customers' concerns. Thus, I include capital, which is defined as the ratio of the sum of total capital and surplus, the asset valuation reserve, and the interest maintenance reserve to total general account assets, measured as of year-end t-1 (Berry-Sto¨lzle, Nini and Wende, 2014).

Size. Smaller firms may have more capacity to grow, suggesting an inverse relation between size and premium growth. However, large firms typically have greater financial capacity to enter into new markets and launch new products (Berger and Bouwman, 2013). Following Cole, Fier, Carson and Andrews (2015), I control for size, which I measure as the natural logarithm of total insurer assets at year-end t-1.

Mutual. Previous studies suggest that a different ownership structure can affect insurers' operation decisions and premium growth as a result (Powell, Sommer and Eckles, 2008; Cole, Fier, Carson and Andrews, 2015). All else equal, mutual insurers may grow more slowly than stock insurers because of limited access to external capital (Powell, Sommer and Eckles, 2008).

Age. Choi (2010) shows an inverse relation between growth and the age of an organization. Thus, organizational age is included.

Liquidity. Liquidity measures a firm's ability to meet its immediate financial obligations. Higher liquidity might help life insurers survive, resulting in better financial strength. However, higher liquidity can also be related to agency problems (Jensen, 1986). Liquidity is defined as the ratio of total cash and investment securities to total assets.

Efficiency. Efficiency is defined as the income-expense ratio. More efficient life insurers are expected to generate more premiums. However, less efficient life insurers might also be associated with higher premium growth rates. Faster growth of less efficient life insurers via subsidies from headquarters might highlight one of the drawbacks of cross-subsidization (Holod and Peek 2011). Efficiency is included to control for investment opportunities at the life insurer level (Cremers, Huang and Sautner 2011).

Capital Issuance and Surplus Note Issuance. Stolzle, Nini and Wende (2014) find that life insurers will issue external capital to support new business and to replace capital exhausted by operating losses. Thus, I include both capital issuance and surplus note issuance; capital issuance is defined as the sum of capital changes paid in and surplus adjustments paid in minus changes in treasury stock divided by general account asset at year end t-1, asset and surplus note issuance consists of the net change of surplus note divided by general account asset at year end t-1.

M&A. Life insurers can grow via mergers and acquisitions (Berger, Demsetz and Strahan, 1999). Thus, life insurers involved in mergers and acquisitions are expected to have higher premium growth rates. To control for the effect of mergers and acquisitions, I include an M&A dummy variable. M&A equals one if an insurer belongs to a different group than it did in a previous year.

A&H focus. Annuity focus and Life focus. A life insurer is viewed as an A&H focus insurer if it earns 75 percent of its premium revenue from accident and health insurance. The same rules are applied to Annuity focus insurers and Life focus insurers.

Premium-Related Control Variables:

Reinsurance and Reinsurance Change. Reinsurance can be ceded by the insurer to other members of the group or ceded to external reinsurers. Both types of reinsurance can help an insurer write more insurance without increasing its surplus (Powell, Sommer and

Eckles, 2008; Cole, Fier, Carson and Andrews, 2015). I control for the insurer's reinsurance by incorporating a net reinsurance variable, measured as total reinsurance assumed minus total reinsurance ceded, divided by total assets at year end t-1 (Cole, Fier, Carson and Andrews, 2015). Reinsurance change is measured by the difference in net ceded reinsurance premiums divided by total assets at year end t-1.

Business Concentration and State Concentration. It is more difficult for financial institutions with riskier product portfolios to increase their market shares because customers have greater concerns about the failure of these firms (Berger and Bouwman, 2013). Like Powell, Sommer and Eckles, 2008, I include Herfindahl-Hirschman indices (HHIs) of premiums written by line of business and by state to proxy for underwriting exposure. The larger the HHIs, the more concentrated (and potentially risky) the insurance product portfolios.

2.4 Empirical Results

2. 4.1 Baseline Results

Insurance premium growth rate results are reported in Table 2.2. Panel A contains direct new premium growth rate results. Some control variables may be simultaneously determined together with premium growth rates, so I separately estimate the effects based on different sets of controls and different fixed effects to reduce endogeneity concerns. Columns (1) to (10) in Panel A present the results based on different specifications.

The coefficients on the interaction term FC×BLFHC in columns (1) – (10) are all positive and statistically significant, which indicates that during the 2008 financial crisis BLFHCs had higher growth rates, which is consistent with the internal market channel increasing premium growth rates. The results are consistent with the transfer hypothesis.

In addition, the BLFHC channel increased the premium growth rates by approximately 16%-19%, which is economically significant.

Table 2.2, Panel B presents net new premium growth rate results. To some extent, net new premium growth rates better reflect the true growth rates of insurance companies because they reflect the true risk exposure owned by insurance companies. The results are consistent with the results in Panel A. The magnitude of the coefficient estimates is smaller but remains substantial as the BLFHC channel helped insurance premium growth by approximately 13–16% during the financial crisis and had a negative impact on premium growth by approximately 7% during non-crisis times.

2.4.2 Premium and Deposit Growth Rate among BLFHCs

If banks transfer customers to affiliated life insurers, we would expect a negative correlation between insurance premium growth rates and deposit growth rates for these BLFHCs. To examine this issue, I present two types of evidence. First, I examine growth rates of deposits and of premiums for BLFHCs at the aggregate level in Figure 1. The figure indicates that aggregate growth rates of premiums and deposits are inversely related for BLFHCs from 2004 to 2011, consistent with BLFHCs transferring customers between banks and life insurers.

I further formalize my analysis by running OLS regressions using data at the group level. I add affiliated banks' deposit growth rate weighted by deposit amount to the baseline regressions presented above. If premium growth and deposit growth are negatively correlated, the coefficients on deposit growth are expected to be negative. Since FDIC insurance coverage for demand deposits increased during the financial crisis, presumably increasing the desirability of such deposits relative to uninsured deposits and annuities. Therefore, I also consider noninsured deposit growth rates which can better capture the customer transfer effect. I present the results in Table 3, Panel D.

The coefficients on deposit growth rates in columns 1–8 are all negative and statistically significant except for columns 1-2. On average, as deposit growth rate increases 10%, the insurance net premium growth rate decreases about 1%, and vice versa. Moreover, the results are stronger among uninsured deposit growth rates. The negative relation between deposits and premiums is consistent with the customer transfer hypothesis within financial conglomerates (Billett and Mauer, 2003; Kuppuswamy and Villalonga, 2015).

2.4.3 Matched Sample Analysis

In section 2.4.1, I assume a linear relation between life insurer characteristics and certain measures of growth. Thus, I have used control variables to separate the effects of internal bank channel from other insurer characteristics. In this section, I relax this assumption by constructing matched BLFHC and non-BLFHC samples.

I use a one-to-one matching method with and without replacement. A probit model is estimated on a 2004 cross section of 116 BLFHC life insurers and 219 non-BLFHC life insurers. The matching life insurer selected is the life insurer with the closest propensity score based on firm age, size, capital level, reinsurance level, liquidity, business concentration, state concentration, efficiency, capital issuance and debt issuance. For a one-to-one with replacement approach, all variables except for reinsurance level are statistically indistinguishable between these two groups (columns 1-4 of Table 2.3, Panel A). For a one-to-one without replacement approach, all variables except for liquidity are statistically indistinguishable between these two groups (columns 5-7 of Table 3, Panel A).

In columns 1-4 of Table 2.3, Panel B, I estimate regressions of premium growth using matched samples of BLFHC life insurers and non-BLFHC life insurers with replacement (columns 1-2) and without replacement (columns 3-4). The results are similar to those in baseline tests. The BLFHC channel is associated with higher insurance premium growth by approximately 13–18 percent during the financial crisis. Overall, my main finding is that during the financial crisis life insurers with bank affiliates grew faster even if I relax the linear relation assumption.

2.5. Additional Evidence and Robustness

2.5.1 Cross-Selling

The transfer hypothesis is based on the argument that annuity products are similar to bank CDs, such that banks can easily promote annuities to potential depositors as a replacement. I separately examine the insurance premium growth rates by product to examine the substitution effects. If customers consider annuity products as substitutes for bank CDs, then the main premium growth effects should be related to annuity products instead of to life or accident and health insurance products. Table2.4 presents the premium growth rate findings for annuity products, life insurance products, and accident and health products. The principal result is that the internal bank channel during the 2008 financial crisis FC×BLFHC has positive and significant effects only on the annuity product premium growth. Economically, the internal bank channel increases the direct new premium growth from annuities by as much as 31% (t-value=2.29) and the net new premium growth from annuities by as much as 30% (t-value=1.95). An internal bank channel does not have statistically significant effects on either life or accident and health products. In summary, these results are consistent with the customer transfer hypothesis.

2.5.2 Cross-Sectional Evidence

The transfer hypothesis assumes that having affiliated banks helps financially constrained life insurers during the financial crisis. In this section, I further analyze what types of life insurers benefit most from the internal banking channel and what types of banks contribute the most premium growth.

Prior research finds that headquarters tend to use internal capital markets to subsidize financially constrained segments (Cremers, Huang, and Sautner, 2011; Billett, and Mauer, 2003, Holod and Peek, 2010). In Table 2.2, Panel C, I reestimate the baseline regression of premium growth in the subsamples of life insurers partitioned by financial constraint level. In columns 1 and 2 of Table 2.2, Panel C, I split my sample at the median value of percentage change of the RBC ratio (2.1%) in whole sample and reestimate my main model of premium growth. For direct and net premium growth, internal banking channel effects hold for weakened life insurers but not for strengthened life insurers. The results reported in Table 2.2, Panel C show that the effects of the internal banking channel are stronger for financially constrained life insurers.

2.5.3 Different Financial Crisis Definition

To further examine the cross-selling effect in 2008, I redefine the financial crisis indicator in several ways and estimate the effects by using the same difference-in-difference framework. Most academic papers define the 2008 financial crisis from 2007 to 2008 or from 2007 to 2009 (Ivashina and Scharfstein, 2010; Cornett, McNutt, Strahan and Tehranian, 2011; Santos, 2011; Kuppuswamy and Villalonga, 2015). In my analysis, the financial crisis indicator equals one in 2008 only. The reasoning behind this is that the meltdown of asset-backed commercial paper and mortgage-backed securities in the summer of 2007 led to massive bank losses (Cornett, McNutt, Strahan and Tehranian, 2011; Santos, 2011). However, during the same period, the stock market continued to perform very well. For example, the return of the S&P 500 Index is approximately 5.5% in 2007. Consequently, investors did not have strong incentives to put their money in banks in 2007. Similarly, the stock market rebounded in 2009 after crashing in 2008 (-43%). The return on the S&P 500 in 2009 is about 26%, and investors are more willing to move into stock markets than to stay in banks.

Table 2.5 presents the results under a different definition of financial crisis. In Columns (2)–(4), the dependent variable is the direct premium growth rate, and the financial crisis indicator equals one in 2007–2008, 2008–2009, and 2007–2009, separately. The coefficients on interaction terms FC×BLHC are not statistically different from zero. These results are consistent with the value of cross-selling only in 2008. The same results are found in the net premium growth rate. My findings are consistent with my hypothesis that the banking channel helped life insurers grow faster in 2008.

2.5.4 Controlling for Lapse Effects

The policy replacement effect can bias the insurance premium growth results. In other words, insurance premium growth could stem from the agents who persuade policyholders to surrender old policies and buy new ones. Previous studies show that reasons to lapse also include needing emergency funds or failing to pay because of personal financial distress (Kuo, Tsai and Chen, 2003). Thus, lapse effects contain more than policy replacement effects. If we find that the BLFHC channel has a positive correlation with the growth rates of the new premium after deducting the surrender amount, we can conclude that the BLFHC channel does help affiliated life insurers. However, if we do not find a positive association, we cannot conclude that the BLFHC channel helps affiliated life insurers through policy replacement.

I redefine the insurance premium growth rate as $\Delta LP_t = LP_t - LP_{t-1}$, where LP_t represents log (premiums minus surrender amounts) in year t for direct and net premiums and truncated growth at -1 and 1. In an unreported table, I find that the BLFHC channel continues to help BLFHC insurers. The coefficients are positive and significant for direct new premium growth rates of approximately10.7% (t-value=1.66) and for net new premium growth rates of approximately 10.7% (t-value=1.88). In short, BLFHC life insurer enjoyed higher premium growth which deducts lapse amount. The results are consistent with the transfer hypothesis.

2.6. Efficiency Analysis

The evidence thus far indicates that life insurers with bank affiliates enjoyed higher annuity premium growth rates during the 2008 financial crisis. These findings are consistent with the customer transfer hypothesis. In this section, I examine whether their resource transfers are efficient by analyzing excess ROA and changes in scope economies.

2.6.1 Excess ROA Analysis

I first examine the excess ROA of BLFHCs to confirm the efficiency transfer. Following Laeven and Levine (2007), I examine whether a BLFHC has a ROA(x) more or less than the ROA(x) it would have had if the BLFHC had been broken down into a portfolio of two entities, each of which specializes in banking or insurance activities of the BLFHC group. In other words, let r^L equal the median ROA of financial institutions that specialized in life insurance activity (a pure-life insurer) and let r^B equal the median ROA of financial institutions that specialized in banking activity (a pure bank). Then activity-adjusted ROA for group j is $r_j = (\alpha_{jL} r^L + \alpha_{jB} r^B)$, where

α_{jL} equals the share of the life insurance activity out of the total activity of the BLFHC group j, measured by total assets and , α_{jB} equals the share of the banking activity in total activity of BLFHC j, measured by total assets. The sum of α_{jL} and α_{jB} equals one. Excess ROA is the difference between a BLFHC's actual ROA and its activity-adjusted ROA. Actual ROA is measured as the BLFHC's asset-weighted average ROA.

Excess ROA_j= ROA $-(\alpha_{jL} r^L + \alpha_{jB} r^B)$.

I consider three different definitions of ROA. ROA (1) is defined as the ratio of earnings before claim payments and taxes to total assets; ROA (2) is defined as the ratio of earnings before taxes to total assets; and ROA (3) is defined as the ratio of net income to total assets.

The first two columns of Table 2.6, Panel A show the median Excess ROA of BLFHCs during non-crisis times and during the financial crisis. During the financial crisis, the median of Excess ROA (1) increased from -0.53% to -0.07%. The difference is significantly different from zero, and the economic change is substantial. The changes in excess ROA (1) support the efficiency hypothesis. However, the other two measures of Excess ROA, which incorporate claim payments, yield a different result. Excess ROA (2) and Excess ROA (3) indicate that BLFHCs performed worse during the financial crisis. For example, the Excess net income to total assets ROA (3), fell from -0.10% during the non-crisis period to -0.47 percent during the financial crisis. Thus, the improvement from the operating side did not outweigh the realized losses and claim payment effects. Overall, BLFHLs performed worse during the 2008 financial crisis.

2.6.2 Scope Economies

If cost, revenue, and profit scope economies for the BLFHCs improved during the 2008 financial crisis, then the results are consistent with the efficiency hypothesis. By contrast, if scope economies for BLFHCs deteriorated, then the results would support the inefficient internal market hypothesis. The data sources for scope economies are from the NAIC and the RIS database of the FDIC. I adopt an approach similar to that taken by Berger, Cummins, Weiss and Zi (2000), Yuan and Phillips (2008) and Berger, Hasan, and Zhou (2010) to measure scope economies. The technique can be decomposed into two stages: (1) the estimation of an appropriate function for a cost, revenue, and profit function by using nonlinear least squares regressions, and (2) measure scope economies at 25th, 50th, and 75th percentiles of the data for each output, netput, and input price during normal times and during the financial crisis. In this section, all financial variables are aggregated at the group level.

Let:

$C_{B1}(y_1; z_1; w_1)$ be the operating cost function for banks specializing in y_1 and z_1,

$C_{L1}(y_2; z_2; w_2)$ be the operating cost function for life insurers specializing in y_2 and z_2,

$C_{JI}(y_1, y_2; z_1, z_2; w_1)$ be the operating cost function for the bank component of BLFHCs,

and $C_{J2}(y_1, y_2; z_1, z_2; w_2)$ be the operating cost function for the life insurance component of BLFHCs,

where w_1 and w_2 are the vectors of input prices relevant to non-BLFHCs. The cost functions of banks specializing $C_{B1}(\bullet)$ and life insurers specializing $C_{L1}(\bullet)$ firms only include the outputs, fixed netputs and input prices relevant to a specialist. The cost functions for each of the divisions of the BLFHCs, C_{JI} $(\bullet)$ and C_{J2} $(\bullet)$, incorporate all the outputs and fixed netputs to allow for interaction effects but exclude the irrelevant prices. The measure of operating cost scope economies is given by

$$S_c(1,2) = \frac{C_{B1}(y_1; z_1; w_1) + C_{L1}(y_2; z_2; w_2) - C_{JI}(y_1, y_2; z_1, z_2; w_1) - C_{J2}(y_1, y_2; z_1, z_2; w_2)}{C_{JI}(y_1, y_2; z_1, z_2; w_1) + C_{J2}(y_1, y_2; z_1, z_2; w_2)}$$

If $S_c(1,2)$ is greater than zero, it indicates that cost scope economies exist. The claim cost, revenue, and profit scope economies are defined similarly to the operating cost scope economies, i.e., they are given by:

$$S_U(1,2) = \frac{U_{L1}(y_2; z_2; w_2) - U_{J2}(y_1, y_2; z_1, z_2; w_2)}{U_{J2}(y_1, y_2; z_1, z_2; w_2)}$$

$S_R(1{,}2)$

$$= \frac{R_{JI}(y_1, y_2; z_1, z_2; w_1) + R_{J2}(y_1, y_2; z_1, z_2; w_2) - R_{B1}(y_1; z_1; w_1) - R_{I1}(y_2; z_2; w_2)}{R_{JI}(y_1, y_2; z_1, z_2; w_1) + R(y_1, y_2; z_1, z_2; w_2)}$$

$S_\pi(1{,}2)$

$$= \frac{\pi_{JI}(y_1, y_2; z_1, z_2; w_1) + \pi_{J2}(y_1, y_2; z_1, z_2; w_2) - \pi_{B1}(y_1; z_1; w_1) - \pi_{I1}(y_2; z_2; w_2)}{\pi_{JI}(y_1, y_2; z_1, z_2; w_1) + \pi(y_1, y_2; z_1, z_2; w_2)}$$

where U (•) the claim cost function, the revenue function R (•) and profit function π (•) are derived in a similar manner as the C (•) function is derived. If $S_U(1{,}2)$ >0, then claim cost scope economies exist. Otherwise, claim cost scope diseconomies hold. If $S_R(1{,}2)$ >0, then revenue scope economies exist. Otherwise, revenue scope diseconomies exist. Similarly, profit scope economies are found if $S_\pi(1{,}2) > 0$, and profit scope diseconomies are found if $S_\pi(1{,}2) < 0$.

Operating cost, claim cost, revenue and profit functions for BLFHCs and non-BLFHCs are separately estimated with the composite functional form. The composite functional form is a quadratic structure for outputs and fixed netputs with a log-quadratic component for input prices, and interaction terms such that separability is not imposed (Berger, Cummins, Weiss and Zi, 2000). This form allows for the possibility that the BLFHCs and non-BLFHCs use different technologies. In addition, the composite production function setting for cost, revenue and profit functions allows zero output for some products and allows negative values for the dependent variables.

The operating cost function is specified as follows:

$$\frac{C}{z_r w_m} = [\sum_{t=1}^{T} \alpha_t D_t + \sum_{i=1}^{n+r-1} \gamma_i q_i + \frac{1}{2} \sum_{i=1}^{n+r-1} \sum_{i=1}^{n+r-1} \gamma_{ij}\, q_i q_j$$
$$+ \sum_{i=1}^{n+r-1} \sum_{k=1}^{m-1} \delta_{ik} q_i v_k] \cdot \exp(\sum_{k=1}^{m-1} \theta_k v_k + \frac{1}{2} \sum_{k=1}^{m-1} \sum_{k=1}^{m-1} \theta_k v_k v_l) + \varepsilon$$

where c = operating cost, D_t = dummy for financial crisis (year= 2008); q_i=y_i/z_r=the ith output divided by the last fixed netput, i=1,…,n; q_i=z_{i-n}/z_r=first r-1 fixed netputs divided by the last fixed netput, i=n+1,…,n+r-1; v_k=ln(w_k/w_m)=natural log of first m-1 input prices divided by the last input price, k=1,…,m-1; $\alpha, \beta, \delta, \gamma, \theta$ are estimated coefficient vectors; and ε is an error term.

The revenue (profit) function is identical to the cost function except that the dependent variable is replaced by claim cost ($\frac{Claimcost}{z_r w_m}$)   revenue ($\frac{Revenue}{z_r w_m}$) and profit ($\frac{Profit}{z_r w_m}$). The composite cost and profit functions are estimated by non-linear least squares.

The dependent variables of the operating cost, claim cost, revenue and profit functions are normalized by the quantity of the last fixed netput (z_r) and the price of the last input (w_m). All the output terms and the first r-1 fixed netput terms are normalized by w_m. z_r is equity capital, and w_m is the price of business services and the labor price of banks. Insurance Operating costs are defined as insurers' operating expenses, including commissions, administrative expenses, licenses, fees, etc. Bank operating costs includes costs of purchased funds, deposits, and labor. Claim costs include all benefits paid by life insurers. Insurance revenues include premium and net investment income[10]. Bank revenue contains interest income and non-interest income. Insurance profits are equal to insurance

[10] In the NAIC life insurer annual statements, cost is line 28 minus line 20 in the "summary of operations" sheet and revenue is line 9 in the "summary of operations" sheet.

revenues minus insurance operating and claim costs. Bank profits are the bank revenues minus bank costs.

The definitions of outputs, inputs and prices are similar to those used in Berger and Mester (1997), Berger, Cummins, Weiss and Zi (2000), Cummis and Weiss, (2001), Yuan and Phillips (2009).

Insurance Outputs, Netputs, and Input prices. I use the sum of incurred benefits plus additions to reserves as a proxy for the first insurance output (proxies for risk-pooling/risk-bearing function and intermediation function). Invested assets (excluding accounts receivable) are employed as the second insurance output, which indicates that insurers provide services in connection with funds by receiving premiums in previous years (intermediation function)[11]. Both outputs are deflated to the base year 2002 using the Consumer Price Index. Reserve and capital are viewed as the fixed netputs. Labor, business services and financial equity capital are three principal groups of insurer inputs. The prices of labor are derived from indices for weekly wages for financial activities from the U.S. Department of Labor (NAICS=5241). The Finance and Insurance Index (2002=1) is from the U.S. Department of Commerce, Bureau of Economic Analysis.

Bank Outputs, Netputs, and Input Prices. The following three types of outputs frequently used in the banking literature are adopted: consumer loans, business loans and securities. Consumer loans are the sum of the dollar value of residential loans, credit card loans, and other installment loans. Business loans represent all other loans, and securities are GTA minus consumer loans and business loans. Physical capital and financial equity capital are considered bank fixed netputs. The price of deposits is measured as the total

[11] Accounts receivable are excluded because the insurer does not have possession of the funds to perform any intermediation function (Berger et al. 2000).

interest expense on the deposits divided by the dollar value of the deposits. The price of labor is calculated as wage per employee. The price of purchased funds is obtained as interest paid on these funds divided by the total dollar value of these funds. Purchased funds include federal funds purchased and other liabilities for borrowed money. Finally, I delete those inputs and outputs with negative values.

Scope Economies Results. Estimates of scope economies are presented in Table 2.7 Panel A. Estimates for operating cost, claim payment, revenue and profit scope economies are evaluated at the first quartile (P25), median (P50) and the third quartile (P75) to avoid the scale-product mix problem (Berger, Cummins, Weiss and Zi, 2000). I find that operating cost scope economies exist at all valuation points but smaller firms are more likely to benefit more from the combination. At the first quartile level of output and input prices, the data reveal that costs economies increased from 13% to 21% during the financial crisis. In addition, at the median and the third quartile levels of output and input prices, cost economies increased from 11% to 21% and from 2% to 11% during the financial crisis, respectively. Similar results are found in revenue scope economies. During the financial crisis, revenue scope economies become even stronger at each valuation point.

However, for the claim payment scope economies, at the first quartile level of output and input prices, the data reveal that claim payment economies decreased from -4.5% to -9.2% during the financial crisis. In addition, at the median and the third quartile levels of output and input prices, cost economies decreased from -4.8% to -10% and from 8.6% to -12.1% during the financial crisis, respectively. The profit scope economies also deteriorate during a financial crisis. Overall, these scope economies results show that BLFHCs enjoy higher operating scope economies and revenue scope economies during the financial crisis than during non-crisis times. However, BKFHCs suffers claim payment and profit scope diseconomies during the same period, these results are more consistent with the inefficient transfer hypothesis.

2.6.3 Regression Analysis

I now address the question of what characteristics of BLFHCs are correlated with the changes in scope economies. I use regression analysis, where the dependent variables are the predicted scope economies for the BLFHCs in the sample and the explanatory variables are the business focus of a bank and its affiliated life insurer. The predicted scope economies are derived from the functions estimated in the previous section for the insurance part of the business and for the banking part of the business. For example, the predicted insurance operating scope economies is defined as

$$S_c(1) = \frac{C_{L1}(y_2; z_2; w_2) - C_{J2}(y_1, y_2; z_1, z_2; w_2)}{C_{J2}(y_1, y_2; z_1, z_2; w_2)}$$

where $C_{L1}(y_2; z_2; w_2)$ is the estimated operating cost function for life insurers specializing in y_2 z_2, $C_{J2}(y_1, y_2; z_1, z_2; w_2)$ is the estimated operating cost function for the life insurance part of BLFHCs, and w_2 is the vector of input prices. There are potentially 298 BLFHC observations for which I can calculate predicted scope economies. After adding group fixed effects and excluding singleton observations, there are 285 BLFHC observations in my sample.

If a bank more focuses on generating fee income than loan income and its affiliated life insurer is an annuity writer, then it indicates that the bank is more likely to sell annuity products, i.e. the substitutes of bank CDs. In addition, the affiliate life insurer is more likely to enjoy the growth of annuity sales during the financial crisis. In this case, the bank shares its customer base with its affiliated life insurer but does not have access to the life insurer's customer base. Thus, I would expect that life insurer revenue scope economies increase with the bank's fee income proportion. In addition, whether insurance profit scope economies grow with these annuity sales depends on whether the annuity sales are profitable products.

Moreover, whether bank revenue and profit scope economies increase depends on the profit margin of fee income. If the profit margin of the annuity fee income is higher than loan income, then the bank revenue and profit scope economies would increase. Otherwise, scope economies decrease because of lower profit margin. The primary independent variables I use to measure fee income activities are Noni and Noni_FC. Noni is the ratio of bank non-interest income to bank total income. Noni_FC equals to Noni times financial crisis dummy (FC). If customer transfers from banks to life insurers occur during a financial crisis, I would expect that the coefficient on Noni_FC should be positive for insurance revenue scope economies. In addition, the coefficient on Noni_FC should be positive for insurance profit scope economies if annuity products contain higher profit margin.

I use Annu_ratio and Annu_ratio_FC to measure the impact of annuity sales on the bank revenue and profit scope economies. Annu_ratio is the ratio of insurance annuity premium to total premium. Annu_ratio_FC equals to Annu_ratio times financial crisis dummy (FC). If a bank's customer transfers are efficient, I would expect a positive coefficient on bank profit scope economies. In contrast, if customer transfers are inefficient, I would expect a negative coefficient on bank profit scope economies. The same expectations apply to the bank revenue scope economies.

I truncate scope economies at -1 and 1. Regression results are presented in Table 2.8 Panel B and Panel C. Consistent with the previous analysis, banks generating higher fee income have positive impacts on insurance revenue and profit scope economies during a financial crisis (Panel B, Column 3 and Column 4). The result is consistent with customer transfers helping life insurers to grow during a financial crisis. Nevertheless, the annuity focus insurance has a negative effect on bank revenue and profit scope economies (Panel C, Column 2 and Column 3), which indicates that the customer transfer in not efficient. The evidence indicates that customer transfers decrease revenue and profit scope economies.

2.7. Conclusion

Previous studies have examined the internal capital markets of financial institutions in the same financial industries (Campello, 2002; Powell, Sommer and Eckles, 2008; Cremers, Huang and Sautner, 2011; Holod and Peek, 2010; Niehaus, 2017). However, internal capital market activities across banks and life insurers have not been previously investigated. I compare the premium growth of BLFHCs and non-BLHCs during the 2008 financial crisis to provide evidence related to the activities of internal capital markets, and I find that during the financial crisis, BLHC life insurers experienced higher premium growth than non-BLHC life insurers, mainly from annuity products. This growth can be attributed to the internal bank channel, i.e., the effects of cross-selling. However, the excess ROA after claim payments and profit scope economies worsen during the financial crisis. It indicates that the marginal return on added capital in life insurers is worse than a bank in the group. In addition, scope economies performed worse for BLFHCs during the 2008 financial crisis. Transferring resources from banks to insurance companies is not efficient for the entire conglomerate.

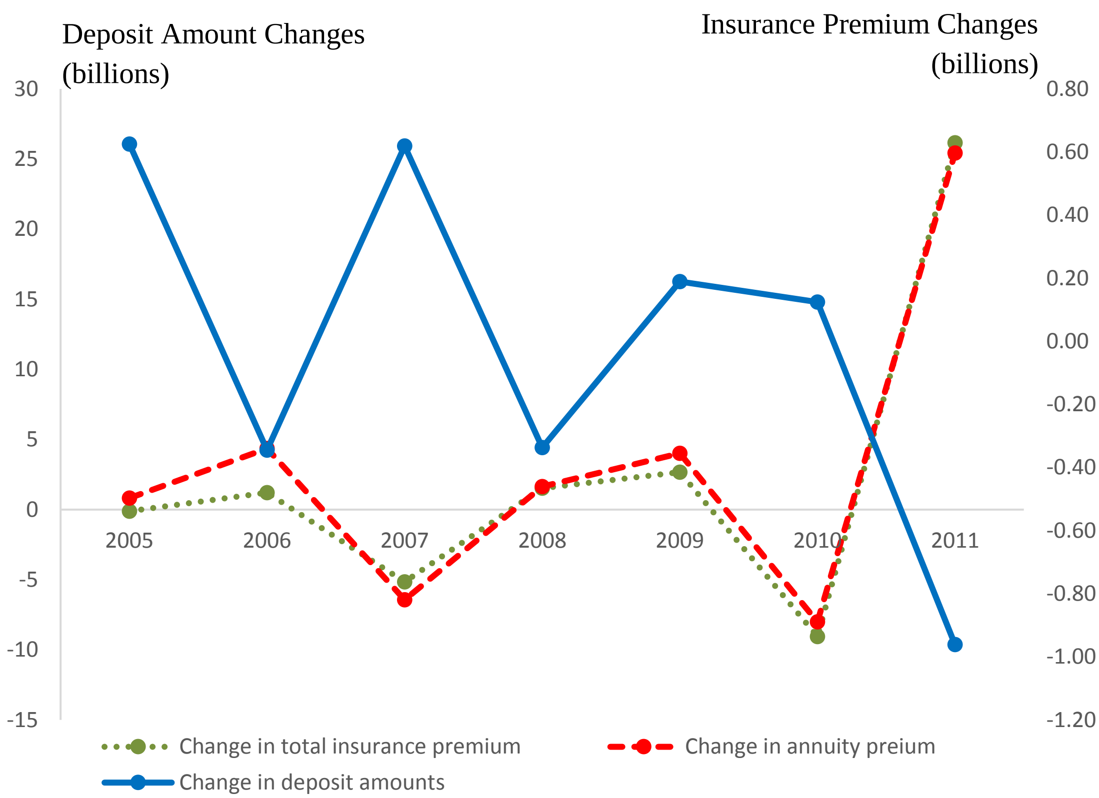

Figure 2.1 Inverse Relationship among Deposit Amounts and Insurance Premiums

This figure presents the relationships among changes in deposit amounts, changes in insurance premiums, and changes in annuity premiums.

Table 2.1 Definition and Summary Statistics

This table reports summary statistics for my sample, which consists of 168 BLFHC life insurers (72 BLFHCs) and 292 non-BLFHC life insurers (189 non-BLFHCs). The sample period covers 2004-2011. The Panel A reported figures describe firm-years. The data are from NAIC annual reports. The panel B of this table reports summary statistics for banking sample, which consists of 110 BLFHC banks (72 BLFHCs) and 7,103 non-BLFHC banks (5,921 non-BLFHCs). The sample period covers 2004-2011. The reported figures describe firm-years. The data are from RIS reports.

Panel A: Life Insurer Characteristics

Variable	Definition	Non-BLFHC life insurers			BLFHC life insurers			Difference (t-Value)
		N	Mean	STD	N	Mean	STD	
Direct New Premium Growth Rate	Growth rate $\Delta P_t = P_t - P_{t-1}$, where P_t represents log premiums in year t for direct premiums and truncated growth at -1 and 1; the growth rates by each line of business are calculated and weighted by the proportion of each business to total business premiums.	1,989	0.030	0.444	768	0.008	0.421	1.19
Net New Premium Growth Rate	Growth rate $\Delta P_t = P_t - P_{t-1}$, where P_t represents log premiums in year t for net premiums and truncated growth at -1 and 1; the growth rates by each line of business are calculated and weighted by the proportion of each business to total business premiums	1,989	0.034	0.449	768	0.006	0.430	1.5
Lnage	The log value of age (in years) of the life insurer	1,989	3.789	0.706	768	3.863	0.715	-2.44
Size	The log value of total insurer assets	1,989	20.083	2.368	768	21.863	2.397	-17.63
Capital	The ratio of the sum of total capital and surplus, asset valuation reserve, and interest maintenance reserve to total general account assets	1,989	0.198	0.168	768	0.227	0.222	-3.69
Capital Issuance	The sum of capital changes paid in and surplus adjustments paid in minus changes in treasury stock divided by general account assets at year end t-1	1,989	0.009	0.052	768	0.020	0.239	-1.95

Variable	Definition	Non-BLFHC life insurers			BLFHC life insurers			Difference
		N	Mean	STD	N	Mean	STD	(t-Value)
Debt Issuance	The net change of the surplus note divided by general account asset on year end t-1	1,989	0.000	0.013	768	0.000	0.003	0.84
Reins	The log value of the total reinsurance assumed minus total reinsurance ceded	1,989	0.076	0.353	768	0.034	0.161	3.19
Reinsurance Change	The difference in net reinsurance premiums ceded divided by total assets on year end t-1	1,989	-0.004	0.146	768	0.002	0.080	-1.18
Liquidity	The ratio of total cash and investment securities to total assets	1,989	0.838	0.190	768	0.688	0.287	15.98
Bus_con	A measure of product concentration, measured by the Herfindahl Index; higher values show greater product concentration	1,989	0.737	0.220	768	0.737	0.223	-0.05
State_hhi	A measure of state premium concentration, measured by the Herfindahl Index; higher values show greater state concentration	1,989	0.316	0.353	768	0.263	0.313	3.65
Efficiency	The ratio of total operating incomes to total costs	1,989	1.151	0.887	768	2.540	16.444	-3.75
M&A	A dummy variable that equals one if mergers and acquisitions happened and zero otherwise	1,989	0.060	0.237	768	0.065	0.247	-0.52
Mutual	A dummy variable that takes a value of 1 if the life insurer is a mutual company	1,989	0.080	0.272	768	0.077	0.266	0.31
A&H_focus	A dummy variable that equals one if the life insurer earns 75% of its premiums from Accident & Health insurance	1,989	0.170	0.376	768	0.060	0.237	7.58
Annuity_focus	A dummy variable that equals one if the life insurer earns 75% of its premiums from Annuity products	1,989	0.161	0.368	768	0.289	0.454	-7.63
Life_focus	A dummy variable that equals one if the life insurer earns 75% of its premiums from life insurance products	1,989	0.299	0.458	768	0.260	0.439	2.01

Panel B: Bank Characteristics

Variable	Definition	Non-BLFHC banks				BLFHC banks			Difference (t-Value)
		N	Mean	STD		N	Mean	STD	
Deposit Growth Rate	Growth rate $\Delta P_t = P_t - P_{t-1}$, where P_t represents log deposit in year t and truncated growth at -1 and 1	46,411	0.072	0.155		474	0.099	0.157	-3.67
Lnage	The log value of age (in years) of the bank	46,411	4.160	0.755		474	3.482	0.758	19.42
Size	The log value of GTA	46,411	11.979	1.313		474	13.989	1.353	-32.55
Capital	The capitalization ratio, defined as equity capital divided by total asset.	46,411	0.106	0.046		474	0.230	0.055	-50.7
Change in Capital	Capital changes divided by total asset on year end t-1	46,411	0.008	0.066		474	0.516	1.043	-10.55
Efficiency	The ratio of total operating incomes to total costs	46,411	1.312	0.256		474	1.329	0.260	-1.46
Liquidity	Cash divided by deposit interest expenses.	46,411	19.307	932.999		474	96.212	932.812	-1.79
Risk	Non-performing loan divided by total loans including unearned income	46,411	0.015	0.024		474	0.022	0.026	-5.98
M&A Index	A dummy variable that takes a value of 1 from the time that the bank acquired another institution and 0 otherwise	46,411	0.037	0.188		474	0.108	0.190	-8.08
Market Share	A bank's total deposit market share	46,411	0.000	0.002		474	0.003	0.002	-32.65

Table 2.2 Panel Regression For Direct (Net) New Premium Growth Rate

OLS regressions with Direct New Premium Growth Rate and Net New Premium Growth Rate as the dependent variables. BLFHC equals one if an insurer belongs to a BLFHC and zero otherwise. FC is a dummy variable, equal to one in 2008 and zero otherwise. The interaction term FC× BLFHC equals one if an insurer belonged to a BLFHC in 2008 and zero otherwise. Firm characteristic control variables include capital, capital issuance, debt issuance, size, mutual, age, liquidity, efficiency, M&A, A&H focus, Annuity focus and Life focus. Premium-related control variables include reinsurance level, reinsurance change, business concentration and state concentration. All control variables are defined in Table 1. Panel A. Regressions with year fixed effects exclude the FC dummy variable. Robust t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. Singleton observations are dropped if fixed effects are added.

Panel A: Direct New Premium Growth Rate

	Direct New Premium Growth Rate									
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BLFHC	-0.022	-0.047**	-0.046*	-0.035	-0.051**	-0.051**	-0.055**	-0.053**	-0.044	-0.041
	(-1.005)	(-1.990)	(-1.943)	(-0.931)	(-2.218)	(-2.187)	(-2.359)	(-2.254)	(-1.151)	(-1.045)
FC		-0.031		-0.022	-0.033	-0.029	-0.031		-0.020	
		(-0.977)		(-0.699)	(-1.058)	(-0.899)	(-0.993)		(-0.638)	
FC× BLFHC		0.191***	0.190***	0.178***	0.193***	0.185***	0.186***	0.185***	0.166***	0.164***
		(3.579)	(3.552)	(3.266)	(3.613)	(3.484)	(3.505)	(3.466)	(3.067)	(3.032)
Capital issuance					0.106		0.108	0.104	0.074	0.069
					(1.059)		(1.101)	(1.098)	(1.005)	(0.991)
Debt issuance					0.908		0.203	0.172	-0.001	-0.047
					(1.262)		(0.184)	(0.155)	(-0.001)	(-0.043)
Capital_lag1					-0.005		0.038	0.035	0.048	0.044
					(-0.070)		(0.498)	(0.450)	(0.415)	(0.374)
Size_lag1					0.006		0.001	0.001	-0.005	-0.006
					(1.010)		(0.180)	(0.173)	(-0.400)	(-0.415)
Mutual_lag1					0.025		0.018	0.021	-0.016	-0.015

					(0.965)		(0.710)	(0.812)	(-0.344)	(-0.307)
Lnage_lag1					-0.018		-0.015	-0.017	-0.006	-0.009
					(-1.072)		(-0.892)	(-0.997)	(-0.232)	(-0.340)
Liquidity_lag1					-0.001		-0.023	-0.018	-0.049	-0.040
					(-0.025)		(-0.458)	(-0.368)	(-0.641)	(-0.536)
Efficiency_lag1					-0.001**		-0.001***	-0.001**	0.000	0.000
					(-2.108)		(-2.748)	(-2.531)	(0.105)	(0.261)
M&A					-0.008		-0.009	0.000	-0.006	0.004
					(-0.195)		(-0.218)	(0.001)	(-0.150)	(0.101)
A&H_focus_lag1					-0.029		-0.007	-0.008	-0.014	-0.016
					(-0.932)		(-0.232)	(-0.262)	(-0.306)	(-0.367)
Annuity_focus_lag1					-0.061**		-0.013	-0.013	-0.016	-0.016
					(-2.119)		(-0.403)	(-0.400)	(-0.408)	(-0.409)
Life_focus_lag1					-0.007		0.020	0.017	0.046	0.041
					(-0.302)		(0.862)	(0.717)	(1.265)	(1.120)
Change_reinsurance						0.527***	0.522***	0.517***	0.570***	0.561***
						(6.355)	(6.304)	(6.334)	(6.483)	(6.462)
Reins_lag1						-0.032	-0.037	-0.036	0.003	0.005
						(-0.941)	(-1.038)	(-1.016)	(0.076)	(0.139)
Bus_con_lag1						-0.188***	-0.198***	-0.197***	-0.324***	-0.324***
						(-4.725)	(-4.492)	(-4.460)	(-5.292)	(-5.298)
State_hhi_lag1						0.007	-0.004	-0.005	-0.036	-0.037
						(0.318)	(-0.157)	(-0.210)	(-0.932)	(-0.973)
Year Fixed Effects	NO	NO	YES	NO	NO	NO	NO	YES	NO	YES
Group Fixed Effects	NO	NO	NO	YES	NO	NO	NO	NO	YES	YES
Clustering by Group	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Observations	2,757	2,757	2,757	2,728	2,757	2,757	2,757	2,757	2,728	2,728
R-squared	0.001	0.005	0.012	0.101	0.010	0.043	0.046	0.051	0.142	0.146

Panel B: Net New Premium Growth Rate

	Net New Premium Growth Rate									
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BLFHC	-0.028	-0.050**	-0.049**	-0.063**	-0.055**	-0.049**	-0.054**	-0.052**	-0.066**	-0.066*
	(-1.369)	(-2.256)	(-2.219)	(-1.977)	(-2.494)	(-2.143)	(-2.352)	(-2.279)	(-1.991)	(-1.926)
FC		-0.025		-0.020	-0.026	-0.024	-0.025		-0.018	
		(-0.758)		(-0.586)	(-0.768)	(-0.707)	(-0.734)		(-0.518)	
FC× BLFHC		0.164***	0.163***	0.147***	0.164***	0.160***	0.160***	0.159***	0.137**	0.136**
		(2.987)	(2.968)	(2.616)	(2.955)	(2.914)	(2.896)	(2.868)	(2.425)	(2.406)
Capital issuance					0.110		0.115	0.111	0.083	0.077
					(0.964)		(1.013)	(1.007)	(0.962)	(0.946)
Debt issuance					1.162		1.027	0.991	0.770	0.707
					(1.287)		(1.074)	(1.022)	(0.864)	(0.791)
Capital_lag1					0.066		0.082	0.081	0.056	0.055
					(0.883)		(1.078)	(1.048)	(0.529)	(0.513)
Size_lag1					0.002		-0.002	-0.002	-0.012	-0.012
					(0.293)		(-0.391)	(-0.354)	(-1.024)	(-0.995)
Mutual_lag1					0.035		0.029	0.030	0.006	0.007
					(1.438)		(1.167)	(1.227)	(0.132)	(0.137)
Lnage_lag1					-0.009		-0.010	-0.011	0.015	0.013
					(-0.589)		(-0.592)	(-0.653)	(0.570)	(0.504)
Liquidity_lag1					-0.002		-0.013	-0.008	-0.085	-0.076
					(-0.033)		(-0.248)	(-0.149)	(-1.200)	(-1.095)
Efficiency_lag1					-0.000		-0.000	-0.000	0.001***	0.001***
					(-0.413)		(-0.585)	(-0.406)	(2.833)	(2.865)
M&A					0.024		0.026	0.035	0.025	0.030
					(0.623)		(0.666)	(0.856)	(0.700)	(0.777)
A&H_focus_lag1					-0.055		-0.034	-0.035	-0.033	-0.035

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					(-1.622)		(-0.953)	(-0.986)	(-0.665)	(-0.720)
Annuity_focus_lag1					-0.052		-0.005	-0.005	-0.003	-0.003
					(-1.636)		(-0.143)	(-0.156)	(-0.061)	(-0.066)
Life_focus_lag1					-0.028		0.002	-0.002	0.029	0.023
					(-1.189)		(0.087)	(-0.084)	(0.795)	(0.641)
Change_reinsurance						0.073	0.060	0.055	0.063	0.056
						(0.711)	(0.578)	(0.527)	(0.560)	(0.499)
Reins_lag1						0.002	-0.011	-0.009	0.003	0.007
						(0.055)	(-0.335)	(-0.265)	(0.074)	(0.191)
Bus_con_lag1						-0.174***	-0.185***	-0.183***	-0.301***	-0.299***
						(-4.282)	(-4.035)	(-3.991)	(-4.742)	(-4.759)
State_hhi_lag1						0.013	-0.011	-0.011	-0.036	-0.035
						(0.633)	(-0.432)	(-0.453)	(-0.965)	(-0.948)
Year Fixed Effects	NO	NO	YES	NO	NO	NO	NO	YES	NO	YES
Group Fixed Effects	NO	NO	NO	YES	NO	NO	NO	NO	YES	YES
Clustering by Group	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,757	2,757	2,757	2,728	2,757	2,757	2,757	2,757	2,728	2,728
R-squared	0.001	0.004	0.012	0.093	0.010	0.012	0.017	0.024	0.108	0.114

Panel C: Cross-Sectional Evidence

Sort criterion	Change in Risk Based Capital Ratio			
Dependent Variable	**Gross New Premium Growth Rate**		**Net New Premium Growth Rate**	
Change in RBC ratio	Weakened	Strengthened	Weakened	Strengthened
Column	(1)	(2)	(3)	(4)
BLFHC	0.052	-0.024	0.031	-0.061
	(1.061)	(-0.350)	(0.490)	(-0.908)
BLFHC×FC	0.184***	0.079	0.172**	0.032
	(2.803)	(0.768)	(2.563)	(0.348)
Control Variables	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Group Fixed Effects	YES	YES	YES	YES
Clustering by Group	YES	YES	YES	YES
Observations	765	1,992	765	1,992
R-squared	0.406	0.210	0.399	0.187

Panel D: Relationship between Insurance Premium Growth Rate and Deposit Growth Rate

	Direct New Premium Growth rate				Net New Premium Growth rate			
	All Deposit		Non-insured Deposit		All Deposit		Non-insured Deposit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Deposit Growth Rate	-0.043	-0.057	-0.077**	-0.077**	-0.090*	-0.102**	-0.109**	-0.115***
	(-0.900)	(-1.248)	(-2.362)	(-2.479)	(-1.883)	(-2.233)	(-2.632)	(-2.900)
Control Variables	YES	NO	YES	NO	YES	NO	YES	NO
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Group Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Clustering by Group	YES	YES	YES	YES	YES	YES	YES	YES
Observations	775	775	775	775	775	775	775	775
R-squared	0.181	0.121	0.184	0.124	0.136	0.117	0.140	0.122

Table 2.3 Panel Regression for Matched Sample and Results

This Table, Panel A provides details on matched samples in my study. I match the closest BLFHC based on propensity scores estimated from a probit model. Panel B shows OLS regression results with Direct New Premium Growth Rate and Net New Premium Growth Rate as the dependent variables. BLFHC equals one if an insurer belongs to a BLFHC and zero otherwise. FC is a dummy variable, equal to one in 2008 and zero otherwise. The interaction term FC× BLFHC equals one if an insurer belonged to a BLFHC in 2008 and zero otherwise. Firm characteristic control variables include capital, capital issuance, debt issuance, size, mutual, age, liquidity, efficiency, M&A, A&H focus, Annuity focus and Life focus. Premium-related control variables include reinsurance level, reinsurance change, business concentration and state concentration. All control variables are defined in Table 1. Regressions with year fixed effects exclude the FC dummy variable. Robust t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Panel A: Propensity Score Matching Diagnostics

		With replacement			Without replacement		
	BLFHC	non-BLFHC	Diff	t-value	non-BLFHC	Diff	t-value
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lnage	3.864	3.918	-0.079	-0.81	3.873	-0.008	-0.09
Size	21.752	21.848	-0.212	-0.72	21.283	0.469	1.71
Capital	0.226	0.205	0.020	0.75	0.191	0.035	1.43
Reins	0.045	-0.001	0.045	2.45	0.037	0.009	0.4
Liquidity	0.688	0.637	0.063	1.59	0.807	-0.118	-3.64
Bus_con	0.716	0.710	0.015	0.55	0.714	0.002	0.09
State_hhi	0.255	0.245	0.038	0.9	0.255	0.000	0.00
Efficiency	2.349	1.101	1.306	1.04	1.248	1.101	0.94
Capital issuance	0.023	0.015	0.010	0.5	0.013	0.009	0.54
Debt issuance	0.000	0.000	0.000	-0.64	0.000	0.001	0.73

Panel B: Panel Regressions for Matched Samples

	Direct New Premium Growth rate	Net New Premium Growth rate	Direct New Premium Growth rate	Net New Premium Growth rate
Replacement	Yes	Yes	No	No
	(1)	(2)	(3)	(4)
FC×BLFHC	0.157**	0.179**	0.134*	0.153**
	(2.046)	(2.323)	(1.882)	(2.080)
BLFHC	-0.023	-0.045	-0.004	-0.030
	(-0.452)	(-1.047)	(-0.082)	(-0.689)
Control Variables	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Group Fixed Effects	YES	YES	YES	YES
Clustering by Group	YES	YES	YES	YES
Observations	1,299	1,299	1,646	1,646
R-squared	0.177	0.162	0.168	0.152

Table 2.4: Regression for Direct New Premium Growth Rate and Net New Premium Growth Rate by Product Line

OLS regressions with Direct New Premium Growth Rate and Net New Premium Growth Rate as the dependent variables. BLFHC equals one if an insurer belongs to a BLFHC and zero otherwise. FC is a dummy variable, equal to one in 2008 and zero otherwise. The interaction term FC× BLFHC equals one if an insurer belonged to a BLFHC in 2008 and zero otherwise. Firm characteristic control variables include capital, capital issuance, debt issuance, size, mutual, age, liquidity, efficiency, M&A, A&H focus, Annuity focus and Life focus. Premium-related control variables include reinsurance level, reinsurance change, business concentration and state concentration. All control variables are defined in Table 1. Regressions with year fixed effects exclude the FC dummy variable. Singleton observations are removed if fixed effects are added. Robust t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Direct New Premium Growth Rate			**Net New Premium Growth Rate**		
	(1)	(2)	(3)	(4)	(5)	(6)
Product	Annuity	Life	Accident &Health	Annuity	Life	Accident &Health
BLFHC	-0.092	0.100	-0.030	-0.099	0.038	-0.049
	(-0.697)	(0.930)	(-0.259)	(-0.806)	(0.303)	(-0.382)
FC× BLFHC	0.313**	0.083	-0.250	0.298*	-0.104	-0.258
	(2.289)	(0.470)	(-1.427)	(1.954)	(-1.007)	(-1.519)
Control Variables	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Group Fixed Effects	YES	YES	YES	YES	YES	YES
Clustering by Group	YES	YES	YES	YES	YES	YES
Observations	2,000	2,523	1,148	1,902	2,421	1,083
R-squared	0.129	0.113	0.177	0.101	0.106	0.196

Table 2.5 Different Financial Crisis Definition

OLS regressions with Direct New Premium Growth Rate and Net New Premium Growth Rate as the dependent variables. BLFHC equals one if an insurer belongs to a BLFHC and zero otherwise. FC is a dummy variable, equal to one in 2008 and zero otherwise. In Columns (2)–(4), the financial crisis indicator equals one in 2007–2008, 2008–2009, and 2007–2009, separately. All control variables are defined in Table 2.1. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Direct New Premium Growth Rate				Net New Premium Growth Rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FC×BLFHC	0.164***				0.136**			
	(3.032)				(2.406)			
FC2× BLFHC		0.043				0.015		
		(1.138)				(0.405)		
FC3× BLFHC			0.031				0.029	
			(0.613)				(0.578)	
FC4×BLFHC				-0.021				-0.031
				(-0.539)				(-0.871)
BLFHC	-0.041	-0.033	-0.030	-0.018	-0.066*	-0.056	-0.058*	-0.043
	(-1.045)	(-0.850)	(-0.759)	(-0.448)	(-1.926)	(-1.612)	(-1.660)	(-1.230)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Group Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Clustering by Group	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,728	2,728	2,728	2,728	2,728	2,728	2,728	2,728
R-squared	0.146	0.144	0.143	0.143	0.114	0.112	0.112	0.112

Table 2.6 Excess ROA of BLFHCs

Excess ROA examines whether a BLFHC has a ROA more or less than the ROA it would have if the BLFHC were broken into a portfolio of two entities, each of which specializes in banking or insurance activities of the BLFHC group. ROA (1) is defined as the ratio of earnings before claim payments and taxes to total assets, ROA (2) is defined as the ratio of earnings before taxes to total assets, and ROA (3) is defined as a ratio of net incomes to total assets. The definition of excess ROA (1) - (3) for a BLFHC is the difference between its actual ROA and its activity-adjusted ROA(1)-(3). All control variables are defined in Table 1, Panel B. Standard errors are adjusted for clustering at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Variable	During Normal Times (1)	During Financial Crisis (2)	Difference (2) – (1) (Rank Sum test)
Median excess ROA (1)	-0.53%***	-0.07%	0.46%**
(p-value for non-parametric sign test)	(0.000)	(0.875)	(-1.99)
Median excess ROA (2)	-0.10%	-0.48%	-0.38%***
(p-value for non-parametric sign test)	(0.128)	(0.430)	(2.35)
Median excess ROA (3)	-0.10%***	-0.47%**	-0.37%***
(p-value for non-parametric sign test)	(0.000)	(0.017)	(2.75)

Table 2.7 Costs, Revenue and Profit Scope Economy Estimates

Note. The sample size used in estimating the BLFHC cost, revenue and profit function is 298. The sample size used in estimating the cost, revenue and profit function for life insurers (non-BLFHC) is 1,205, and the sample size for banks (non-BLFHC) is 39,748. The valuation points for the life insurance variables are based on both BLFHCs and non-BLFHCs that write annuity products, and the valuation points for the bank variables are based on both FHCs and non-FHCs that operate bank business. A sign test is used to examine the statistical difference. *, **, and *** denote significance at the 10%, 5%, and 1% levels

Panel A: Main Results

	Operating cost scope economies			Claim cost scope economies			Revenue scope economies			Profit scope economies		
	Normal Time	Financial Crisis	Diff	Normal Time	Financial Crisis	Diff	Normal Time	Financial Crisis	Diff	Normal Time	Financial Crisis	Diff
Q1	13.3%	21.3%	8.0%***	-4. 5%	-9.2%	-4.8%***	-1.5%	1.9%	3.4%***	-21.1%	-53.9%	-32.8%***
Median	10.6%	20.6%	10.0%***	-4.8%	-10.0%	-5.2%***	4.8%	7.6%	2.8%***	22.3%	1.9%	-20.4%***
Q3	1.9%	11.0%	9.1%***	8.6%	-12.1%	-20.7% ***	18.9%	18.7%	-0.2%***	58.9%	44.6%	-14.3%***

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Panel B Insurance Scope Economies Regression Analysis

OLS regressions with scope economies as the dependent variables. Regressions with group fixed effects. *Non-Int* is the ratio of non-interest income to total bank income. Financial Crisis is a dummy variable, equal to one in 2008 and zero otherwise. Singleton observations are dropped. Robust t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

VARIABLES	(1) Operating Cost Scope Economies	(2) Claim Cost Scope Economies	(3) Insurance Revenue Scope Economies	(4) Insurance Profit Scope Economies
Financial crisis	-0.0001	-0.0001	-0.0012	0.0001
	(-0.372)	(-0.372)	(-1.374)	(0.381)
Non-Int	0.0006	0.0006	0.0089	0.0022**
	(1.380)	(1.380)	(1.215)	(2.162)
Non-Int × Financial crisis	0.0001	0.0001	0.0036*	0.0015***
	(0.329)	(0.329)	(1.804)	(2.970)
Annu_ratio	0.0003	0.0003	-0.0024	-0.0000
	(0.922)	(0.922)	(-1.098)	(-0.066)
Annu_ratio × Financial crisis	0.0002	0.0002	-0.0047***	-0.0016***
	(0.760)	(0.760)	(-3.203)	(-2.925)
Observations	285	285	285	285
R-squared	0.377	0.377	0.681	0.545

Panel C Bank Scope Economies Regression Analysis

OLS regressions with scope economies as the dependent variables. Regressions with group fixed effects. *Annu_ratio* is the ratio of annuity premium to total insurance product premiums. Financial Crisis is a dummy variable, equal to one in 2008 and zero otherwise. Robust t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

VARIABLES	(1) Bank Cost Scope Economies	(2) Bank Revenue Scope Economies	(3) Bank Profit Scope Economies
Financial crisis	0.1043***	0.1758***	0.1623**
	(3.016)	(2.752)	(2.674)
Non-Int	0.0196	-0.0165	-0.0470
	(0.114)	(-0.091)	(-0.245)
Non-Int × Financial crisis	-0.3379***	-0.1905	-0.2193
	(-3.687)	(-0.948)	(-1.255)
Annu_ratio	-0.2001	-0.1606	-0.1613
	(-1.585)	(-1.267)	(-1.296)
Annu_ratio × Financial crisis	-0.1364**	-0.2796**	-0.2422**
Observations	285	285	285
R-squared	0.678	0.568	0.561

CHAPTER 3

CORRELATED TRADING BY LIFE INSURERS AND ITS IMPACT ON BOND PRICES[12]

3.1 Introduction

Academics, insurance professionals, and regulators continue to debate whether traditional insurance activities of insurers are a source of systemic risk.[13] For example, the Financial Stability Oversight Council (FSOC) in December of 2014 designated MetLife as a systemically important financial institution (SIFI) despite objections from Metlife and other commentators (see e.g., Wallison, 2014). Metlife challenged the ruling, and in March 2016, a judge rescinded the SIFI designation. The Department of Justice on behalf of FSOC has appealed the decision.[14] One argument for why life insurers are a source of systemic risk is that life insurers have investments of over $2.5 trillion in bonds and that their trading activity is correlated within the industry, i.e., life insurers herd.[15] As a consequence, life insurers have the potential to disrupt financial markets by causing or exacerbating security price movements away from fundamental values. Schwarcz and Schwarcz (2014) forcefully make this argument and call for greater regulation (also see FSOC (2013), Getmansky et al. (2016), and Koijen and Yogo (2016)).[16]

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[12] Chia-Chun Chiang and Greg Niehaus. Submitted to Journal of Risk and Insurance 12/2/2016.
[13] Many commentators acknowledge that non-traditional activities, such as trading credit default swaps, could cause insurance groups to be systemically important (see e.g., Cummins and Weiss, 2014 and Harrington, 2009).
[14] MetLife maintains a website containing documents filed related to the debate. See https://www.metlife.com/sifiupdate/index.html.
[15] Data are from the 2015 Life Insurers Fact Book.
[16] Note that there are other arguments for how insurers could contribute to systemic risk, including concerns

On the other side of the spectrum from those who argue that life insurer investment herding contributes to systemic risk, Vaughan (2012) argues that the life insurance industry provides a stabilizing force in financial markets during times of crisis. This would occur, for example, if during liquidity shocks that induce sales from other institutions, insurers maintain their positions and/or even step in on the buy side. A related point of view is that insurer investment decisions are unlikely to influence security prices because, even though life insurers' asset portfolios are large, they are typically buy and hold investors; i.e., their trading activity is much lower than their holdings. Paulson and Rosen (2016) report that the annual turnover rate of corporate bonds held by life insurers is about one-fifth that of corporate bonds in general. On the other hand, trading in corporate bonds is relatively thin in general, and so even a relatively small amount of trading can potentially impact prices. Indeed, recent evidence by Ellul et al. (2011) and Merrill (2014a and 2014b) is consistent with life insurer investment behavior impacting security prices.

Despite the debate regarding the impact of life insurer investment decisions on financial markets, there is little research that focuses on the extent to which life insurers herd, and if they do, on whether insurer herding is likely to be disruptive to financial markets. Exceptions are Cai et al. (2012 and 2016), who analyze herding in bond markets by mutual funds, pension funds, and both property-liability and life insurers. Related studies also include Getmanksy, et al. (2016), who examine the interconnectedness of insurance companies' investment decisions using cosine similarity, and Paulson and Rosen (2016),

about an insolvency of one insurer reducing confidence in the ability of other insurers to make good on their promises, which in turn could cause policyholder runs and cause insurers to liquidate assets quickly and at fire sale prices. See Foley-Fisher, et al. (2015) and Fenn and Cole (1994). Cummins and Weiss (2014) focus on whether reinsurance activities contribute to systemic risk. Also see Acharya et al. (2014), Billio et al. (2012), Chen et al. (2012), Manconi et al. (2012), Neale, et al. (2012), Weiss and Muhlnickel (2014), and Weiss, et al. (2015).

who examine the extent to which insurers provide liquidity to the investment grade corporate bond market.

Conceptually, there are several reasons why one might expect herding behavior to exist among life insurers. First, life insurers face common accounting and regulatory rules.[17] As a result, one might expect insurers to respond in similar ways (buy or sell the same securities) to changes in these institutional rules and to changes in how a security is treated under these rules. As an example of the latter situation, if a downgrade of a security increases the required risk-based capital that an insurer must hold, then insurers would likely have greater incentives to sell the security. Second, insurers' financial condition and future prospects are likely to be impacted in similar ways by general economic information (such as changes in interest rates and credit spreads) and to information about the value of specific types of securities. Consequently, insurers might be expected to adjust their portfolios in similar ways in response to economic information. Third, the information cascades theory suggests that company fund managers infer the value of securities from the trades of other fund managers, which in turn leads fund managers to mimic other fund managers' trades (Bikhchandani et al., 1992). Fourth, if the labor market for fund managers assesses ability using relative fund performance, then fund managers will be concerned about poor performance when other funds have good performance. To avoid this outcome, fund managers might mimic each other (Scharfstein and Stein, 1990). Finally, insurers often outsource the management of some of their assets (Kim et al., 2015). As a consequence, the trading activity of insurers using the same outside asset manager could be correlated. Our main purpose is not to distinguish among these various

[17] It is also worth noting that often these rules differ from those that apply to other financial institutions, which makes an analysis of life insurers as a group of interest.

explanations for herding; instead we identify bond and insurer characteristics that are associated with life insurer herding and examine the impact of life insurer herding on bond prices.

To investigate whether life insurers' corporate bond investment decisions exhibit herding behavior over the 2002-2011 time period, we utilize two herding measures. One is the classic measure introduced by Lakonishok, Shleifer and Vishny (1992), hereafter, the "LSV" measure, which measures the extent to which insurers tend to buy the same securities or sell the same securities within a given time interval using the number of buy trades relative to total trades. The other herding measure, introduced by Oehler and Chao (1990), equals the absolute value of insurers' buy volume minus their sell volume divided by total insurer volume in the bond. Hereafter, we refer to this measure as the volume-based herding measure. As is common in the herding literature, we examine trading behavior over quarterly time intervals.

It is important to highlight that the LSV herding measure does not incorporate information about the volume of trading in a particular bond. In addition, the LSV measure for a particular bond during a given quarter measures whether insurers' buying or selling of that bond differs from the overall buying or selling in all of the bonds in which insurers transacted during that quarter. In other words, by controlling for aggregate trading of life insurers, the LSV herding measure indicates whether insurers are trading a particular bond differently than insurers are trading bonds in general. In contrast, the volume herding measure for a particular bond simply measures whether insurers as a group are on one side of the market (buy or sell side) in that particular bond. The volume herding measure is therefore analogous to the order imbalance measures used in the literature on the impact of equity market herding on stock prices (e.g., Chordia, et al., 2002 and Dorn et al., 2008).

Our evidence is strongly consistent with life insurer herding. The overall average LSV herding measure for individual corporate bonds is 10.2 percent, which indicates that on average life insurers are about 10.2 percent more likely to be on the same side of the market for individual bonds (either on the buy or sell side) than would be expected if their buy versus sell decisions were independent and consistent with insurer trading of all bonds. We also calculate the buy LSV herding and sell LSV herding measures, as proposed by Wermers (1999). The overall buy and sell LSV herding measures for individual corporate bonds have an average value of 11.1 and 9.4 percent, respectively, indicating that herding by life insurers is not concentrated on one side of the market. The volume based measures also indicate that on average life insurers herd. For example, when insurer buy volume exceeds insurer sell volume in a bond, it does so on average by a multiple of 3.6, and when insurer sell volume exceeds insurer buy volume in a bond, it does so on average by a multiple of 4.5.

We also examine how the herding measures vary with bond and insurer characteristics. We find that herding by life insurers is greater in smaller bonds and lower rated bonds. This evidence is consistent with herding being more likely when there is greater asymmetric information about the bond's value, which is consistent with the information cascades theory of herding (Bikhchandani et al., 1992). We also find that sell-side herding is greater in bonds that have been recently downgraded, which is consistent with risk-based capital requirements increasing insurers' cost of holding bonds with greater credit risk.

We also investigate the association between herding and "SIFI insurers," i.e., insurers that are part of a group that has been designated as a systemically important financial institution (SIFI). The Financial Stability Oversight Council (FSOC) has designated three insurers (AIG, MetLife, and Prudential) as systemically important.[18] Our objective is to provide evidence on whether SIFI insurers are associated with herding behavior and its impact on bond prices. The evidence indicates that, holding other factors constant, herding is on average greater in bonds in which SIFI insurers have a relatively high proportion of the trading volume. Thus, a necessary condition for SIFI insurers to be systemically important through the investment herding channel seems to be satisfied – SIFI insurers are associated with investment herding.

Life insurer herding, of course, does not necessarily imply that the herding behavior of life insurers impacts bond prices. There are, however, conditions under which correlated trading is more likely to be stabilizing or destabilizing. We therefore provide evidence on whether these conditions are present when insurers exhibit herding behavior. Correlated trading by life insurers is more likely to be destabilizing if the herding is consistent with momentum trading, i.e., if insurers tend to buy when prices are increasing and sell when prices are decreasing. In this case, insurer trading activity can exacerbate price movements away from fundamental values (see Bank of England, 2014). The opposite pattern would be consistent with insurers' correlated trading providing a stabilizing influence on bond markets (Vaughn, 2012).

We provide two types of evidence on whether insurers' herding is consistent with momentum trading. In panel regression analysis of herding measures, we find that sell

[18] As noted above, MetLife's SIFI status is being contested in the courts.

herding measures increase as negative abnormal returns increase in magnitude and as positive abnormal returns increase in magnitude. Using a different methodology, we compare the abnormal returns on portfolios of bonds that have large buy or sell herding measures to portfolios that do not have large buy or sell herding measures. This approach reveals that sell-side herding tends to occur following negative abnormal returns. Additional analysis suggests that this momentum trading is especially strong during the financial crisis.

We also examine abnormal returns on the portfolios in the quarter during and the quarter subsequent to the herding behavior in an effort to examine whether there is evidence of herding impacting bond prices. The results provide some evidence that abnormal returns of portfolios with high sell herding are significantly lower during the herding period than the abnormal returns of portfolios of bonds with low sell herding, especially during the financial crisis and when insurers that are part of a group that has been designated as a SIFI trade the bonds. However, we do not find that the returns rebound in the subsequent quarter, which is what one would expect if the insurer sell herding was temporarily distorting prices. Thus, the evidence is more consistent with insurer sell herding helping to impound information into prices.

The papers most related to this study are by Cai et al. (2012 and 2016). As stated earlier, Cai et al.'s papers examine mutual funds, pension funds, and insurance companies (both property-liability and life companies); whereas, we provide a more focused investigation of herding by life insurers and incorporate insurer characteristics in the analysis. One of the results of the two papers differ: We do not find price reversals following herding;

whereas Cai et al. (2016) do find price reversals on average. As discussed later in the paper, we investigate a variety of potential explanations for the different findings.

The paper proceeds as follows. In the next section, we briefly review the literature on herding. The methodology and data are presented in sections 3.3 and 3.4. We present descriptive results on how herding varies with bond characteristics, insurer characteristics, and time in Section 3.5. Panel regression analysis of herding measures are presented in Section 3.6, followed by the analysis of portfolio returns in Section 3.7. We end with a summary of the evidence and a discussion of the implications for issues related to the systemic risk of life insurers.

3.2 Background on Herding

3.2.1 Determinants of Herding

One explanation for herding among a group of firms in the same industry is that each institution is affected in similar ways by economic information and therefore they each respond to economic information in the same manner (Froot et al., 1992). Correspondingly, insurers that are similar in terms of their products, size, capitalization, and profitability are likely to be impacted similarly by economic information. Consequently, we examine the extent to which herding is related to these insurer characteristics.[19]

According to the information cascade theory, some institutions infer information from the trades of other institutions and therefore mimic the trading of other institutions

[19] Understanding the types of insurers that herd is relevant to identifying insurers that contribute to and/or are exposed to systemic risk. Evidence from Weiss and Muhlnickel (2013) indicates that an insurer's contribution to systemic risk is largely explained by insurer size; whereas, an insurer's exposure to systemic risk is explained by size, the proportion of net revenue earned from investment activities, and proportion of non-policyholder liabilities to total liabilities.

(Bikhchandani et al., 1992). Assuming information about smaller bonds (those with a relatively small amount outstanding) and less liquid bonds is more costly to obtain, investors would be more likely to infer information from other institutional investors about these bonds (see Wermers, 1999 and Sias, 2004). According to this explanation, herding would be greater in smaller bonds and less liquid bonds.[20]

There is a growing literature providing evidence that accounting and risk-based capital rules induce insurers to trade in similar ways. For example, Ambrose, et al. (2008, 2012), Ellul et al. (2011), Ellul et al. (2014), and Merrill, et al. (2014b) examine how risk-based capital and accounting rules influence insurers' incentives to sell securities that have been downgraded. Merrill, et al. (2014a) and Becker and Ivashina (2013) examine insurers' incentives to reach for yield within risk-based capital categories. Becker and Opp (2014) and Hanley and Nikolova (2014) respectively examine how insurers' investment decisions changed after the NAIC lowered the risk-based capital requirements for non-agency residential mortgage backed securities (RMBS) in 2009 and for non-agency commercial mortgage backed securities (CMBS) in 2010. Consistent with this literature, we examine whether a bond's rating and the level of insurers' risk-based capital is associated with herding behavior.

Kim et a. (2015) report that outsourcing of investment management services by insurers has increased over the past decade and that over 65 percent of the insurers in the highest

[20] Another explanation for institutional herding arises from managerial agency problems. Scharfstein and Stein (1990) show that if managers' performance across firms is influenced by common factors and that managers care about their reputations for being a good manager, then the labor market will assess a given manager's performance conditional on the performance of other managers. This, in turn, induces a fund manager to mimic other fund managers so that he/she does not "standout" from the group if performance is poor. Dasgupta et al. (2011a) build on this idea in their model of the price impact of herding. Cross-sectional predictions from this framework relate to portfolio managers' characteristics, such as manager compensation, age, and experience. Unfortunately, we do not have this type of information.

quartile of assets have employed at least one investment advisor. If different insurers employ the same investment advisor, then the investment advice received across these insurers will likely be correlated, which in turn will likely lead to correlation in investment decisions.

3.2.2 Empirical Evidence on Institutional Herding

The majority of the literature on institutional herding examines equity markets.[21] Lakonishok, et al. (1992) introduced the herding measures that we use and that most of the herding literature uses. We refer to these measures as LSV herding measures. They find some evidence that pension funds herd over quarterly periods, although the herding is not strong. Wermers (1999) finds essentially the same results using data on mutual funds. Instead of looking for herding within a quarter, Sias (2004) examines whether herding occurs across quarters. Consistent with institutional herding, Sias (2004) finds that institutional buying in one quarter is correlated with institutional buying in the prior quarter, i.e., herding is persistent from one period to the next. Dasgupta et al. (2011b) also document the persistence of herding behavior.

A number of papers have examined the relationship between herding and the returns earned during the period prior to the herding period, the herding period, and the period subsequent to the herding period. Although there is some variation across the studies, Grinblatt et al. (1995), Wermers (1999), and Nofsinger and Sias (1999) find that positive (negative) stock returns are associated with institutional buy (sell) herding in the period prior, during, and subsequent to when the herding takes place, consistent with momentum

[21] In addition to institutional herding, there are also studies examining herding by individual investors. See for example, Dorn et al. (2008), who examine retail clients of a large German discount broker, Barber, et al. (2009a, 2009b), who examine clients of two U.S. discount brokers, and Feng and Seasholes (2004), who examine Chinese investors.

trading. Sias (2004) finds that herding is not positively associated with prior period returns once he controls for prior period herding. Dasgupta et al. (2011) also show that persistent herding is negatively correlated with long horizon returns. Gutierrez and Kelly (2009) document similar results.

There are fewer studies that examine herding in bond markets.[22] Oehler and Chao (2000) examine herding by 57 German mutual funds in bonds grouped by similar characteristics and find low LSV herding measures, on average. They also introduce a herding measure based on volume and find greater herding using the volume based measure than the LSV measure. We adopt their volume based measure.

The papers most similar to this paper are by Cai et al. (2012 and 2016). Cai et al. (2012 and 2016) use changes in quarterly holdings to calculate LSV herding measures; whereas, we use transaction data to calculate both the LSV herding measures and the volume based herding measures introduced by Oehler and Chao.[23] Cai et al. (2012) focus on how herding is influenced by the Financial Industry Regulatory Authority's (FINRA) requirement that bond market trading information be made public. Cai et al. (2016) focus on the extent to which herding is persistent and whether such persistency is due to institutions following themselves or other institutions. In addition, Cai et al. (2016) examine, as we do, abnormal bond price changes around herding. As discussed more below, we find different results than Cai et al. (2016) with regard to the abnormal returns in the post-herding period.

[22] The Global Financial Stability Report (2015) reports that herding by both bond and equity mutual funds increased in 2014 relative to 2009.

[23] Provided Cai et al. (2016) use the face value of holdings changes, as opposed to the market value of holdings, the difference between transactions within a quarter (which we use) and changes in holdings over a quarter (which they use) should be minimal.

3.3 Two Herding Measures

3.3.1 LSV Measures

We begin by describing the herding measure for a group of investors that was originally proposed by Lakonishok, et al. (1992). In the following description, the investor group could be the entire group of insurers in our sample or a particular subset of insurers selected based on specific characteristics. Let

$\#B_{i,t}$ = the number of insurers from the investor group that were net buyers of bond i during time period t.

$\#S_{i,t}$ = the number of insurers from the investor group that were net sellers of bond i during time period t.

Of all of the insurers from the investor group that transacted in bond i, the proportion that were net buyers is the insurers' buy ratio for security i during period t:

(1) $p_{i,t} = \#B_{i,t} / (\#B_{i,t} + \#S_{i,t})$.

The idea is to test whether the insurers' buy ratio for security i is different than what would be expected given the purchasing and selling activity of the investor group across a broader set of securities. Thus, $p_{i,t}$ is compared to the overall buy ratio during period t, denoted p_t, for a class of securities to which bond i belongs. For example, if security i is a corporate bond with an investment grade rating, then p_{it} could be compared to the overall buy ratio of all investment grade rated bonds. The overall buy ratio is defined as follows:

(2) $p_t = \frac{\sum_i \#B_{i,t}}{\sum_i \#B_{i,t} + \sum_i \#S_{i,t}}$.

The absolute difference, $| p_{i,t} - p_t |$, indicates whether the proportion of net buyers of security i differs from the proportion of net buyers in the class of securities.

If insurers' buy versus sell decisions were independent and modeled as a binomial random variable with probability p_t, then the expected value of the absolute difference, $| p_{i,t} - p_t |$, would be positive. Consequently, an adjustment factor is subtracted from the absolute difference to create the herding measure for security i during period t with an expected value of zero:

(3) $LSV\_HM_{i,t} = | p_{i,t} - p_t | - AF_{i,t}$,

where

(4) $AF_{i,t} = \sum_{j=0}^{N_{i,t}} \left| \frac{j}{N_{i,t}} - p_t \right| \binom{N_{i,t}}{j} p_t^{j} (1 - p_t)^{N_{i,t}-j}$,

and $N_{i,t}$ is the number of insurers transacting in security i during period t.[24] As $N_{i,t}$ increases, the adjustment factor declines. For example, if $p_t = 0.5$ and $N_{i,t}$ equals three, the adjustment factor is 0.25, but if $N_{i,t}$ equals 25, the adjustment factor is 0.0806.

Intuitively, a positive value for the herding measure indicates that the group of insurers tend to trade a particular bond in the same direction more than would be expected if their buy versus sell decisions were independent and the probability of a buy equaled the overall buy ratio for insurers during the time period. By averaging the herding measures over time and/or securities, we test whether insurers tend to trade in the same direction, i.e., herd. In addition, we use panel regressions to examine variables that are associated with the herding measure.

[24] To illustrate the calculation of the adjustment factor, suppose that there are three insurers transacting in a particular bond and that the probability of a buy transaction (p_t) is ½. Then there are four possible outcomes for the buy ratio: 0, 1/3, 2/3, and 1. The probabilities of these outcomes are 1/8, 3/8, 3/8, and 1/8, respectively. Consequently, the expected value of the absolute difference between the buy ratio and ½ equals

$$\{ | \tfrac{0}{3} - \tfrac{1}{2} | \tbinom{3}{0} \left(\tfrac{1}{2}\right)^0 \left(\tfrac{1}{2}\right)^3 + | \tfrac{1}{3} - \tfrac{1}{2} | \tbinom{3}{1} \left(\tfrac{1}{2}\right)^1 \left(\tfrac{1}{2}\right)^2 + | \tfrac{2}{3} - \tfrac{1}{2} | \tbinom{3}{2} \left(\tfrac{1}{2}\right)^2 \left(\tfrac{1}{2}\right)^1 + | \tfrac{3}{3} - \tfrac{1}{2} | \tbinom{3}{3} \left(\tfrac{1}{2}\right)^3 \left(\tfrac{1}{2}\right)^0 \} =$$

(1/16 + 1/16 + 1/16 +1/16) = ¼, which is the adjustment factor.

Wermers (1999) introduced a buy and a sell herding measure, denoted LSV_BHM and LSV_SHM, by conditioning on whether the security had a higher (lower) buy ratio than the average buy ratio. That is,

$\text{LSV\_BHM}_{\text{it}} = \text{LSV\_HM}_{\text{it}}$ if $\text{p}_{\text{it}} > p_t$ and undefined otherwise,

$\text{LSV\_SHM}_{\text{it}} = \text{LSV\_HM}_{\text{it}}$ if $\text{p}_{\text{it}} < p_t$ and undefined otherwise.

Appendix A provides a simple example to illustrate the calculation of the LSV herding measures.

3.3.2 Incorporating the Information on the Size of Trades

The LSV herding measures take into account the number of trades, but not the size of the trades. Thus, a $50,000 buy transaction is treated the same as a $50 million buy transaction. To incorporate the size of the transaction, we utilize a herding measure used by Oehler and Chao (2000), which takes into account the volume of buy trades and sell trades by insurers. The herding measures based on volume for bond i in quarter t equals the absolute value of the difference between the amount purchased by insurers and the amount sold by insurers as a proportion of the total amount transacted by insurers:

(5) $\text{VOL\_HM}_{it} = |\text{ Amt Purchased}_{it} - \text{Amt Sold}_{it}| \,/\, [\text{ Amt Purchased}_{it} + \text{Amt Sold}_{it}\ ]$.

This measure is similar to the order imbalance measures used in a number of equity market studies (see e.g., Chordia et al. (2002)). Analogous to the buy and sell LSV herding measures, we also calculate buy and sell herding measures based on volume and denote them by VOL_BHM and VOL_SHM, respectively. VOL_BHM (VOL_SHM) is the value of the VOL_HM if buy volume of insurers is greater (less) than sell volume by insurers.

In addition to taking into account the amount transacted, the herding measure based on volume differs from the LSV herding measures in that it does not subtract a benchmark measure of insurer buy versus sell volume in the bond market. Stated differently, unlike the LSV measures, the volume based measure does not control for the general movement of insurers in or out of bonds. Instead, the volume based measures incorporate aggregate shifts of insurers in and out of bonds.

3.4 Data

We examine insurer transactions in individual bonds over quarterly time periods starting in the first quarter of 2003 and ending in the fourth quarter of 2011.[25] The data are from Schedule D, Parts 3, 4, and 5 of insurers' annual statements, which report information on bonds that the insurer purchased during the year (Part 3), sold during the year (Part 4), and bought and sold during the year (Part 5). As reported in Row 2 of Table 3.1, after deleting non-market secondary transactions and those observations without a reported cusip or a transaction date, there are close to 2.3 million bond transactions reported by 1,148 different life insurance companies in 315,961 different bonds issued by 48,864 issuers.[26] For each transaction, the variables reported include cusip, transaction date, type of purchaser (including non-market counterparties such as matured, transferred, called, etc.), cost, par value, and market value.

The transaction data are merged with the Fixed Investment Securities Database (FISD), which provides bond characteristics, including issuance date, maturity date, amount outstanding, coupon rate, and rating history. Following Cai et al. (2012), we restrict the sample to bonds that (a) have remaining maturity greater than two quarters (because bonds

[25] The TRACE data are available starting in the third quarter of 2002, but there are relatively few bonds in TRACE for the 3rd quarter of 2002. Since we require return data for the prior quarter, we begin the analysis in the first quarter of 2003.

[26] Non-market transactions are defined by the listed counterparty having one of the following titles: maturity, call, exchange, in-house, pay-down, tax write-off full redemption internal transfer, tender, merged, dividend, basis spinoff, mortgage, or corporate reorganization.

with remaining maturity less than two quarters will necessarily leave the insurer's portfolio over the coming quarter), (b) were issued at least three quarters prior (to avoid potential new issue effects), (c) have a fixed coupon,[27] (d) are corporate bonds denominated in U.S. dollars (because bond characteristics are missing for most of the other bonds). The number of bonds in the sample drops to 17,316 as a result of this step.

The data are then merged with the Trade Reporting and Compliance Engine (TRACE) data to obtain liquidity, volume, and return measures. Following Bessembinder, et al. (2009) and Dick-Nielsen (2014), we exclude canceled trades, corrected trades, reversal trades, and commission trades. We also follow Rossi (2014) and delete observations that most likely have errors in reported prices.[28] These procedures reduce the number of bonds to 13,689.

The data are also merged with insurer annual statement data to obtain insurer characteristics, such as size and capitalization measures. Insurers with missing or negative value for surplus, total assets, or net premiums written are excluded, which reduces the number of bonds to 12,875. Since most of our analysis will utilize prior quarter bond returns, we drop observations for which we cannot calculate the prior quarter return. The resulting sample has 12,165 bonds traded by 908 life insurers. Recall that the LSV herding measures are calculated using the percentage of buy transactions by insurers in a period (quarter). To ensure that we estimate the buy ratio with some precision, we impose the restriction that each bond in the sample in a given quarter must have transactions from five

[27] The data do not include information about the interest formula for variable coupon bonds.
[28] Specifically, we eliminate bond prices with a 50% return reversal (i.e., if the bond price is preceded or followed by a price change of more than 50%) and if the absolute difference between the price and the median price over the prior 10 transactions and subsequent 10 transactions is "large," which is defined using the median of all of the price differences relative to the median of the 20 transactions (i.e., the median of the absolute deviations, denoted by MAD). Specifically, we eliminate observations if the absolute difference between the price and the median price over the 20 transactions is greater than $1 + $5*MAD.

different insurers. This gives us 176,541 bond transactions in 5,752 bonds by 904 life insurers. The empirical analysis is conducted at the bond-quarter level; there are 20,760 such observations (not tabulated) meeting the screens in Table 3.1.

In Table 3.2, we present descriptive statistics for the bond-quarter observations that are used in the subsequent analysis. On average, the bonds transacted are 4.1 years old and had an average maturity when issued of 13.9 years. The average (median) face amount is \$860.3 (\$551.5) million. Credit Rating takes a value between one and ten, where one indicates the lowest rating (in default) and 10 indicates the highest rating (AAA). To calculate a bond's credit rating, we use the average of three major credit rating agencies ratings and assign the bond to a rating category as described in the Table 3.3.[29] The average (median) credit rating is 6.9 (7.0) and 67.0 percent of the bonds transacted have an investment grade rating (i.e., above BB).

We calculate a bond's quarterly abnormal return by taking the bond's total return and subtracting the return on a benchmark bond portfolio that consists of bonds with similar ratings and maturity. Our approach to calculating the abnormal return is similar to Bessimbinder et al. (2009).[30] More specifically, we construct matching portfolios (benchmark portfolios) using all of the bonds in TRACE that can be matched to FISD and that do not have a rating change during the quarter. We classify bonds using the 10 rating categories (AAA, AA, … C, Default) described above and either three or four maturity categories depending on whether the bond is investment grade (rated BBB or higher) or

[29] We also used the NAIC ratings and the regression results reported below are essentially the same.
[30] If T is the start of the quarter, then the previous quarter abnormal return equals

$$\frac{(P_{i,T-1}+AI_{i,T-1})-(P_{i,T-91}+AI_{i,T-91})+C}{(P_{i,T-91}+AI_{i,T-91})} - \frac{I_{i,T-1}-I_{i,T-91}}{I_{i,T-91}},$$

where $P_{i,T-x}$ is the bond price on day T-x (x days before the start of the quarter), $AI_{i,T-x}$ is accrued interest on day T-x, and C is the coupon payment(s) received. $I_{i,T-x}$ is the matching portfolio value x days before the start of the quarter.

not. For investment grade bonds, the maturity categories are 1 to 3 years, 3 to 7 years, 7 to 10 years, and 10 or more years. For non-investment grade bonds, the categories are 1 to 7 years, 7 to 10 years, and 10 or more years.[31] This yields 34 benchmark portfolios. We then subtract the return on the bond in each quarter from the return on the corresponding benchmark portfolio to find the abnormal return. If a bond's rating category changes during a quarter, then we change the benchmark portfolio to be a weighted average of the benchmark corresponding to the different rating categories. The average winsorized abnormal return (at the 1 and 99 percent levels) during the quarter prior to the quarter in which herding is measured is -0.4 percent.

To measure the characteristics of the insurers transacting in the bonds in each quarter, we calculate the weighted average of each insurer's characteristic (e.g., ROA), where an insurer's weight is the proportion of total insurer volume in the bond during the quarter due to that insurer. The average (median) number of insurers transacting in a given bond in a quarter is 7.8 (7.0). The average (median) winsorized risk-based capital ratio (RBC) is 8.4 (8.1). The distribution of insurer asset size is skewed with a mean of $43.8 billion and a median of $32.3 billion. The average and median return on assets (ROA) is 0.9. The average proportion of volume from insurers that are part of a group that has been designated as a systemically important financial institution (SIFI) is 0.2. Using 75 percent of premiums written in one line of business as an indicator of product line focus, the average proportion of volume from insurers that focus in life insurance is 13 percent; the average proportion of volume from insurers that focus on annuity business is 39 percent;

[31] These maturity categories reflect those used by Yield Book indices, which were used as benchmarks in robustness checks.

and the average proportion of volume from insurers that focus in accident and health insurance is 9 percent.

3.5 Descriptive Analysis of Herding

Table 3.4 reports the average herding measures for our sample. The average LSV herding measure (LSV_HM) equals 10.2 percent, which indicates that life insurers' tend to buy the same bond or sell the same bond more so than would be expected if their buy and sell decisions were independent. The LSV buy herding measure for the overall sample is 11.1 percent and the LSV sell herding measure for the overall sample is 9.4 percent. These results indicate that the herding behavior of life insurers is not concentrated on the buy or sell side of the market. Instead, both buy and sell decisions are correlated across life insurers.[32]

Also reported in Panel A of Table 3.4 are the herding measures based on insurer volume of buy and sell transactions. On average, the overall volume herding measure, VOL_HM, is 60.5 percent, indicating that on average insurers are on one side of the market in bonds. The average buy volume herding measure is 56.5 percent, which indicates that when insurers' buy volume exceeds sell volume, the average buy volume is about 3.6 times the sell volume.[33] The average sell herding measure based on volume is 63.7 percent, which indicates that when insurers' sell volume exceeds buy volume, the average sell volume is 4.5 times the buy volume. The correlation coefficient between the overall herding measure based on volume, VOL_HM, and the LSV herding measure, LSV_HM, is 0.54.

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[32] If all of the bonds in the initial sample with five transactions are used to calculate the herding measures (98,906), as opposed to those that went through the various data screens outlined in Table 3.1, the herding measures are higher: LSV_HM = 14.4 percent, LSV_BHM = 11.1 percent, and LSV_SHM = 17.5 percent. If we require only three transactions each quarter instead of five transactions, then the herding measures are lower.
[33] If buy (sell) volume is denoted by B (S), then the volume-based buy herding measure is (B-S)/(B+S). If this measure equals k, then B = S(1+k)/(1-k). If k=.565, then B=3.6 S.

To put the herding measures in perspective, Panel B of Table 3.3 reports selected results from the prior literature on herding for other types of institutional investors, securities, and time periods. Generally, the evidence indicates that institutional investors have relatively small herding measures for stock transactions (see e.g., Lakonishok et al., 1992 and Wermers, 1999). However, the evidence on bond transactions by institutional investors by Cai et al. (2016) indicates much higher herding measures, consistent with our results.

To provide descriptive evidence on the herding measures, we present a series of graphs in which the LSV herding measures and the volume-based herding measures are plotted versus selected variables. Figures 1 and 2 report herding measures for subsets of bonds based on bond size and bond ratings, respectively. For these analyses, the expected buy ratio (p_t) is the buy ratio for all of the bonds within the category of bonds being considered, as opposed to the buy ratio for all bonds, as was used in herding measures reported in Table 3. For example, in Figure 1, which reports the average herding measure for bonds in four size (amount outstanding) categories, the expected buy ratio for each size category uses only the bonds within that category.

Figure 3.1 illustrates that the average LSV herding measures are highest for bonds with the lowest amount outstanding (between zero and $20 million) and that the average LSV herding measures decline as the amount outstanding increases. Figure 3.2 presents the volume-based herding measures for the different bond size categories. The volume-based herding measures also decrease on average as the amount outstanding increases. These results are consistent with existing studies that institutional herding is significantly greater in small stocks. One explanation is that small bonds have less public information, and therefore life insurers are more likely to make decisions based on other insurers' behavior, consistent with informational cascades (Bikhchandani et al., 1992).

Figure 3.3 and 3.4 illustrates that the average LSV herding measures are lower for investment grade compared to non-investment grade bonds. The volume-based herding measures also indicate that herding is greater in non-investment grade bonds. Several factors could explain this relationship. First, if non-investment grade bonds have greater information asymmetry, which induce insurers to mimic trades of other insurers, then herding would be greater in non-investment grade bonds (Bikhchandani et al., 1992). Second, because of the higher risk-based capital requirements of non-investment grade bonds, insurers (especially those with lower capital) will have an incentive to sell bonds that are downgraded from investment grade to non-investment grade (see Ambrose et al., 2008 and 2012, and Ellul et al., 2011 and 2012). Third, buy herding could result from financially strong insurers purchasing bonds that have been downgraded and that are experiencing downward price pressure from other institutions that are selling these bonds.[34]

Figure 3.5 and 3.6 illustrates how the average herding measures vary over time. For this analysis, the expected buy ratio (p_t) for the LSV herding measures is calculated using all of the bonds in the sample, as was done in Table 3.4. Both the LSV and the volume-based average herding measures increase gradually from 2004 through 2009. After reaching a peak in 2009, the average herding measures decrease in 2010 and 2011. Thus, there is some evidence that herding by insurers increased during the financial crisis.

[34] See Paulson and Rosen (2016) for analysis of whether life insurers bond transactions provide liquidity in general and during the financial crisis.

3.6 Panel Regressions of Herding Measures

3.6.1 Explanatory Variables

To examine variables that are related to herding in a multivariate context, we present a panel regression analysis of the bond herding measures. The dependent variable is either the overall herding measure (LSV_HM_{it}), the sell herding measure (LSV_SHM_{it}), or the buy herding measure (LSV_BHM_{it}) for bond i during quarter t or the corresponding volume-based herding measures (VOL_HM_{it}, VOL_SHM_{it}, VOL_BHM_{it}). The list of explanatory variables, which includes bond and insurer characteristics, is given in Table 3.2 with descriptive statistics. We also include bond and quarter fixed effects to control for time-invariant unobservable bond characteristics and time effects that may affect the herding level.

We are particularly interested in the coefficient on PrRet, the bond's abnormal return in the previous quarter. A positive coefficient on PrRet in the buy herding regression would be consistent with greater buy herding following price increases and a negative coefficient on PrRet in the sell herding measure would be consistent with greater sell herding following price decreases. Either of these results would be consistent momentum trading by insurers, which would raise concerns about insurers exacerbating price movements.

Table 3.2 includes several variables that describe a bond's rating and whether the rating has changed in the quarter. As described earlier, the variable Rating ranges from one to 10; it has a mean value of 6.9. The variable InvGr is a dichotomous variable indicating whether the bond is investment grade (BBB or higher) or not; 72.6 percent of the bonds are investment grade. In the regression analysis, we include a linear spline of the rating level with a knot at the investment grade cutoff. This allows the sensitivity of herding measures to vary based on whether the bond is investment grade or not. We also include upgrade and downgrade dummy variables to examine whether new information about the bond's rating influences herding in the quarter of the rating change.

Regarding insurer characteristics, it is useful to highlight two points. First, the insurer financial characteristics are measured as of the prior year end. Second, the insurer characteristics are a weighted average of the values for the insurers that transacted in the bond during the quarter, where an insurer's weight is the proportion of volume in the bond during the quarter due to that insurer. We examine whether the herding measures are related to average insurer size, return on assets, and risk-based capital ratios of the insurers transacting in the bond. Instead of imposing a linear relationship between the herding measures and the average risk-based capital ratios, we include two dichotomous variables; one variable indicates whether the average risk-based capital is less than seven and the other indicates whether the average risk-based capital ratio is between seven and nine. These cutoff values roughly correspond to the 25th and 75th percentile values for the weighted average risk-based capital ratios. We also control for the number of insurers transacting in the bond during the quarter.

In addition, we include a variable, SIFI, which measures the proportion of insurer transaction volume in the bond during the quarter from insurers that are part of a group that has been designated as a systemically important financial institution (i.e., AIG, MetLife, and Prudential). There are on average 27 insurers across the sample quarters from these three groups. The estimated coefficient on this variable indicates whether SIFIs tend to be involved in herding.

3.6.2 Regression Results

The results of six panel regressions are reported in Table 3.4. Regarding bond characteristics, the multivariate analysis reinforces some of the relationships found in the univariate descriptive analysis. First, overall herding and sell herding is greater in smaller bonds, as the coefficient on AmtOutst is negative and statistically significant in each of the HM and SHM regressions. Second, the coefficients on the Rating variables indicates that as the bond's rating increases, the herding measures decline, on average. The negative relation between herding and ratings is stronger, both economically and statistically, for sell herding than buy herding and for non-investment grade bonds than investment grade bonds. We can reject that the coefficients on Rating1 and Rating2 are equal for in the overall herding regressions, but not in the sell or the buy herding regressions.

The coefficients on UpGr and DownGr give the estimated impact on herding of a change in the bond's rating during the quarter. We find a significant positive effect of upgrades on the overall and buy volume herding measures. Downgrades are associated with a significant increase in sell herding and a decrease in buy herding. On average, a downgrade is associated with a higher LSV (volume-based) sell herding measure of 2.7 (5.1) percent. These findings are consistent with the literature that indicates that insurers tend to sell downgraded bonds (Ambrose et al. (2008, 2011) and Ellul et al. (2011)).

We use a linear spline specification to examine the impact of prior abnormal returns on herding. The knot on the spline is at zero, which allows the relationship between herding and prior abnormal returns to differ when abnormal returns are negative versus positive. For the buy herding and overall herding regressions, we do not find much evidence of a relationship between herding and prior abnormal returns. For sell herding, however, we find a negative relationship when abnormal returns are negative and a positive relation when returns are positive, which is statistically significant for the volume sell herding measure. Thus, the more negative are abnormal returns, the stronger is sell herding. And, the more positive are abnormal returns, the stronger is sell herding.

Regarding insurer characteristics, the coefficient on the SIFI indicator variable is positive and statistically significant in five of the six regressions, suggesting that herding is greater when insurers that are part of groups that are designated as a SIFI trade the bond, all else equal. Also, there is some evidence that herding tends to be greater when insurers with relatively low RBC ratios trade the bond, all else equal.

Some of the insurer characteristics have a different relationship with the LSV versus the volume-based herding measures. For example, insurer size is negatively associated with the LSV herding measures, but positively associated with the volume-based herding measures, holding other factors constant. The positive association between insurer size and the volume based herding measure is not surprising given larger insurers will, all else equal, have greater trade volumes. Also, the number of insurers transacting in the bond is positively associated with the LSV measures, but negatively associated with the volume-based measures. A likely explanation for these relationships is that the LSV herding measures tend to be larger when a larger number of smaller insurers transact in the bond and that the volume-based herding measures tend to be large even when a small number of large insurers trade a high volume of bonds. Finally, the herding measures based on volume are positively associated with the annuity focus variable, suggesting annuity providers are associated with buy herding.

3.6.3 Robustness Checks

To examine the impact of the financial crisis on herding, we estimate the regression models for the financial crisis period (2008-2009) separately from the non-financial crisis period (2002-2007, 2010-2011) and use a Chow test to examine whether the coefficients are significantly different in the two periods. To conserve space, we do not tabulate the results. In general, we cannot reject that the coefficient estimates are the same during the financial crisis versus the non-financial crisis. We do find in each of the regressions, a few variables with significantly different coefficient estimates during the financial crisis, but we do not find a consistent pattern that yields an economic interpretation.

We also investigate whether the impact of downgrades on the herding measures depends on whether the rating change crossed the investment grade threshold or not. We find that the positive relationship between downgrades and sell herding as presented in the regressions in Table 3.4 is not attributable only to downgrades that cross the investment grade threshold. That is, similar effects are observed for downgrades that cross the investment grade threshold and downgrades that do not.[35]

Finally, we examine whether herding measures are affected by whether we use company level or group level data. For the measures used to this point, if two companies in the same group buy the same bond in the same quarter, they are considered as two separate buy transactions. One might argue that if investment decisions are made at the group level then these two transactions should be consolidated and treated as one buy transaction, which would result in lower LSV herding measures. If indeed investment decisions are made at

[35] In addition, we investigate whether herding is greater when a bond rating change is not preceded in the prior quarter by a prior rating change in the same direction versus when a bond rating change follows a rating change in the same direction in the previous quarter. We refer to the former rating changes as first mover rating changes. We find that both first mover rating downgrades and non-first mover rating downgrades are positively associated with sell herding. See Bewart et al. (2014) for an analysis of the timing of rating changes.

the group level, then herding measures based on the consolidated transactions of insurers in the same group might more accurately reflect the extent to which independent organizations herd.

Table 3.6 presents the average herding measures when the transactions of insurers in the same group are consolidated. We refer to these as the consolidated herding measures. The average LSV consolidated herding measures are about half the magnitude of those reported in Table 3.4. For example, the average overall herding measure reported earlier is 10.2 percent and the one reported in Table 3.6 is 5.7 percent.[36] The volume-based herding measures are also lower than those reported in Table 3.4. For example, the sell herding measure reported earlier is 63.7 percent and the one reported in Table 3.6 is 59.4 percent. We also estimated the regression models using the group herding measures and found that most of the relationships revealed by the regressions in Table 3.5 also hold if group herding measures are used.[37]

3.7 Relation between Herding and Bond Abnormal Returns

3.7.1 Overview

We further examine whether life insurer herding is related to past returns using a methodology similar to that employed by Barber et al. (2009) and Dorn et al. (2008) in their studies of equity market herding. Cai et al. (2016) use a similar approach. We place

[36] The number of bonds used to calculate the average herding measures in Table 3.6 is substantially lower than the number of bonds used to calculate the average herding measures reported in Table 3.4. The reason is that we require five transactions from different organizations in a quarter for a bond to be included in the sample and consolidation of transactions reduces the number of bonds meeting this requirement. Thus, part of the difference in the average herding measures could be due to the sample of bonds used. Indeed this is the case. If we restrict the bonds to those used in Table 3.6 but do not consolidate transactions of insurers in the same group, then average herding measures are roughly midway between those reported in Table 3.6 and those reported in Table 3.4.

[37] One exception is that we find that the coefficients on the SIFI variable are statistically significant in only two of the six estimated regression equations.

bonds into portfolios each quarter based on their herding measures and examine whether abnormal returns during the quarter prior to portfolio formation differ between portfolios with high herding measures versus low herding measures.

This methodology also allows us to examine abnormal bond returns during the quarter in which herding occurs (the portfolio formation quarter) and in the subsequent quarter market. Regarding returns during and subsequent to the herding period, there are at least four possible findings and corresponding interpretations:

1. Positive (negative) abnormal returns during the quarter in which buy (sell) herding occurs followed by zero abnormal returns in the subsequent quarter would be consistent with insurers having better information about the value of bonds and that their herding helps to incorporate that information into the price of the bonds.
2. Positive (negative) abnormal returns during the quarter in which buy (sell) herding occurs followed by negative (positive) abnormal returns in the subsequent quarter would be consistent with insurer herding causing prices to move away from fundamental values during the herding quarter and then subsequently return to their fundamental values.
3. Zero abnormal returns during the quarter in which buy (sell) herding occurs followed by positive (negative) abnormal returns in the subsequent quarter would be consistent with insurers having better information about the value of bonds, but that their herding does not impact pricesr.
4. Zero abnormal returns during the quarter in which buy (sell) herding occurs followed zero abnormal returns in the subsequent quarter would be consistent with insurer herding not having an impact on the market.

3.7.2 Methodology

We place bonds in portfolios based on their buy and sell herding measures and we conduct separate analyses for the portfolios formed using LSV herding measures and the portfolios formed using the volume-based herding measures. For each quarter, we divide all of the bonds in the sample in two categories: (1) those with a non-missing buy herding measure and (2) those with a non-missing sell herding measure. The bonds in the first category are then divided into quintiles based on the magnitude of their buy-herding measures. Portfolio B1_LSV (B1_VOL) consists of the bonds with the lowest buy herding measures in each quarter using the LSV (volume-based) buy herding measure. Portfolio B5_LSV and B5_VOL consists of the bonds with the highest buy herding measures. We repeat the same ranking procedure for bonds with non-missing sell-herding measures, creating portfolios S1_LSV (S1_VOL) to S5_LSV (S5_VOL), where portfolio S1_LSV (S1_VOL) consists of the bonds with lowest LSV (volume-based) sell herding measures in each quarter and S5_LSV (S5_VOL) consists of the bonds with the highest LSV (volume-based) sell herding measures each quarter.

Table 3.7 provides information about the portfolios formed using the LSV measures and Table 3.8 provides information about the portfolios formed using the volume-based measures. The second and third columns of each Table provide descriptive information about the average number of bonds and the average herding measure in the portfolio over the sample period.[38] The other three columns report the average abnormal returns on each portfolio in (1) the quarter prior to portfolio formation, (2) the quarter in which the portfolio

[38] The average number of bonds in the various portfolios can vary slightly due to the way that ties (bonds with the same value of the herding measure) are treated and because the number of bonds with non-missing buy and sell herding measures varies by quarter.

is formed, and (3) the quarter after the portfolio is formed. Our focus is on the difference in the abnormal returns between the portfolios with high buy (sell) herding, i.e., B5 and B4 (S5 and S4) and the portfolio with the lowest buy (sell) herding, i.e., B1 (S1). In other words, we are interested in the differential impact of high buy (sell) herding versus low buy (sell) herding on bond returns. This approach also helps to control for common factors affecting bond returns during a quarter that are not captured by our benchmark portfolios.

Focusing first on Table 3.7, the average buy herding measure in B5_LSV is 36.2 percent and the average sell herding measure in S5_LSV is 29.8 percent, both of which suggest a substantial degree of herding in the bonds in these portfolios. Portfolios B4_LSV and S4_LSV have average herding measures of 20.9 percent and 20.7 percent, respectively; these numbers also suggest a high degree of herding in the bonds in these portfolios. In contrast, portfolios B1_LSV and S1_LSV have LSV herding measures that are negative, indicating little herding in the bonds in these portfolios. Similarly, Table 3.8 indicates that B5_VOL and B4_VOL have high average buy herding measures based on volume and S5_VOL and S4_VOL have high average sell herding measures based on volume; whereas, B1_VOL and S1_VOL have low herding measures.

For each of these 10 portfolios and for each of the 36 quarters, we calculate the equally-weighted abnormal returns for the quarter before, the quarter of, and the quarter after the portfolio formation quarter. The abnormal returns are calculated using a matching portfolio methodology similar to that in Bessembinder, et al. (2009).[39] This is repeated for each bond in the herding portfolio for each quarter and the resulting values are averaged to

[39] As is well-known, the secondary corporate bond market in general exhibits thin trading, i.e., many bonds do not trade on a daily basis. In addition, not all transactions are reported in TRACE (our source of bond price information). Consequently, when no transaction is reported in the TRACE data for one of the days of interest to us, we use the nearest prior transaction price in TRACE.

calculate the average abnormal return for the portfolio for that quarter. These quarterly average abnormal returns are then averaged over the 36 quarters to calculate the overall average abnormal return for each of the 10 portfolios. To account for heteroscedasticity in the abnormal returns, we base statistical significance on standardized abnormal returns using a sign-rank test (Ederington et al. 2014).[40]

3.7.3 Results

Table 3.7 reports the average abnormal returns for each of the 10 portfolios and the difference in abnormal returns for the portfolios with high herding and low herding. For the high buy herding portfolios, B5_LSV and B4_LSV, the abnormal returns are not statistically different from the abnormal returns for the low buy herding portfolio (B1_LSV) in any of the time periods, except for subsequent quarter.

The high sell herding portfolios, S5_LSV and S4_LSV, however, have abnormal returns that are statistically different from the abnormal returns for the low sell herding portfolio (S1_LSV) in the quarter prior to portfolio formation. For the quarter prior to portfolio formation, the difference in the abnormal return between S5_LSV and S1_LSV is -1.39 percent, which is large economically and statistically significant at the one percent level. This finding indicates that bonds in which insurers exhibit strong sell herding behavior tend to have lower returns in the prior quarter than bonds in which insurers do not exhibit sell herding, which is consistent with sell herding occurring in bonds that have recently performed poorly.

[40] We use the cross-sectional standard deviation to scale the abnormal returns. Ederington et al. (2014) recommend using both cross-sectional and time series measures of standard deviation, but given that we use quarterly data over nine years, we do not have enough time series observations to incorporate a time series standard deviation for the first part of our sample period.

For the herding period, the difference in abnormal returns between S5_LSV and S1_LSV and also between S4_LSV and S1_LSV are negative, large economically, but not statistically significant. There is no evidence that there is a rebound in prices in the subsequent quarter relative to bonds with no herding. Indeed, the S5_LSV – S1_LSV portfolio continues to have negative abnormal returns in the subsequent quarter (although not statistically different from zero). Thus, the evidence does not suggest price pressure effects that are relieved in the subsequent quarter.

The results when herding is defined using volume are presented in Table 3.8. Consistent with the previous results, this evidence indicates that buy herding is not associated with abnormal returns in the prior quarter. However, we find positive abnormal returns in the herding quarter, but no subsequent reversal. This is consistent with buy herding helping to incorporate information into prices.

The results using sell herding based on volume indicates negative abnormal returns in the quarter prior to portfolio formation, which again is consistent with sell herding by insurers following poor returns. Our evidence also indicates large negative abnormal returns in the herding quarter, Again, we do not find abnormal performance in the subsequent quarter when herding is defined using volume. Thus, the evidence is not consistent with sell herding pushing prices below fundamental values.

Our results differ from Cai et al. (2016) who find significant price reversals following sell side herding by mutual funds, pension funds, and insurance companies. In light of Cai et al.'s results, we conduct a number of robustness checks:

(1) We extended our post-herding period to two quarters and also to three quarters, but we still do not find evidence of reversals.

(2) The analysis above uses transaction prices to calculate abnormal returns; whereas, Cai et al. (2015) use Merrill Lynch quoted prices. To explore whether transaction prices versus quoted prices explain the different results, we gather quoted prices from Bloomberg. We are able to download historical Bloomberg quoted prices only for bonds that were still outstanding as of September 2016. Consequently, this sample is smaller than our main sample and consists of longer maturity bonds than the main sample. The results are summarized in Table 3.9. Although the statistical significance of the results using quoted prices differ somewhat from our baseline results (presented in Table 3.7 and 3.8), the implications are similar, i.e., (a) sell side herding is preceded by negative abnormal returns, (b) during the herding period, there is evidence of positive abnormal returns for buy herding and negative abnormal returns for sell herding, (c) no evidence of price reversals in the post herding period. Note that this analysis does not completely rule out the possibility that the explanation for the different results is the use of different price data, as our quoted prices are from a different source than Cai et al. (2016).

(3) Our method of calculating abnormal returns differs from Cai et al. (2016). We therefore redo our analysis using raw returns; a summary of the results is presented in Table 3.10. The raw return results are similar to those using abnormal returns, except that we find large positive returns in the quarter following portfolio formation for the high sell herding portfolios relative to the low sell herding portfolios using both the LSV and the volume based herding measures. In only one instance, however, is the difference between the high and low sell herding portfolios statistically significant at

the 10 percent level.[41] Given the statistical evidence is weak and conceptual arguments for using abnormal returns as opposed to raw returns are strong, we place relatively little weight on these results. Nevertheless, the analysis suggests that a potential explanation for our results differing from Cai et al. (2016) is the different benchmarks used to calculate abnormal returns.

3.7.4 Life Insurers Selling and then Buying the Same Bond

Another way of detecting evidence of bond prices moving away from fundamental values during strong herding periods is to examine whether insurers view that the bonds are mispriced, as indicated by their trading behavior. Specifically, we examine whether insurers who sell bonds when there is strong sell side herding are more likely to buy the same bonds in the subsequent quarter than insurers who sell bonds during quarters with weak sell side herding. For this analysis, for each quarter we place bonds into five portfolios based on their LSV sell herding measure (LSV_SHM), as we do in the abnormal return analysis. We then calculate the percentage of bonds in each portfolio that are purchased in the subsequent quarter by the same insurers that sold the bonds during the portfolio formation quarter. Finally, we calculate the mean percentage that were subsequently purchased across all of the quarters in the sample.

The results for the five portfolios, which are labeled as S1_LSV to S5_LSV (with S5_LSV being the portfolio with the highest LSV herding measure), are reported in Panel A of Table 3.11. The corresponding results for the portfolios formed using the volume sell

[41] Another possible explanation for the different results is that the method of testing for statistical significance differs between the two studies. As noted earlier, we use the cross-sectional standard deviation to scale the abnormal returns when testing for statistical significance (see Ederington et al. (2014)). Cai et al. (2016) do not report how they calculate statistical significance. If we do not standardize abnormal returns, then the raw returns in the quarter after sell herding reported in Table 9 are statistically significant at the 5 and 10 percent level.

herding measure are presented in Panel B. The results clearly indicate that the percentage of bonds that were sold and then subsequently purchased by the same insurer declines as we move from low sell-side herding (S1) to high sell-side herding (S5), contrary to what one would expect if insurers viewed prices moving away from fundamental values during periods of high sell-side herding. Thus, insurers are not more likely to buy bonds that they previously sold during high herding periods.

3.7.5 Impact of the Financial Crisis

One might argue that if insurer herding were to impact prices, it would be most likely to occur during periods when financial markets are in turmoil. Therefore, we redo the bond price analysis for the period before, during, and after the financial crisis. The use of quarterly data inhibits an in-depth analysis of this issue because of the few number of observations during the financial crisis and therefore the weak power of any statistical tests. Nevertheless, in Table 3.12 we report the results of the portfolio analysis for three separate time periods: 2002-2007, 2008-2009, and 2010-2011. Given the relatively few observations in each period, we focus on economic magnitudes in our discussion. The results are not substantively changed if we define the financial crisis as the third quarter of 2007 to the end of 2009.

The striking feature is the large negative abnormal return during the financial crisis for the bonds with high sell herding (S5) relative to bonds with low sell herding (S1) during the quarter before herding. The difference in these portfolios is -3.77 percent when the LSV measures of herding are used and -2.58 percent with the volume-based herding measure. Thus, the evidence suggests that sell herding following poor bond performance was especially pronounced during the financial crisis. The abnormal return results during the financial crisis for the quarter after sell-side herding occurs are mixed. For example, using the LSV herding measure, the differences between the abnormal returns for the high sell-side herding portfolios and the low sell-side herding portfolio, S5-S1 and S4-S1, are -0.90 percent and 1.44 percent, respectively. While neither difference is statistically significant, the -0.90 percent abnormal return suggests no price reversal, but the 1.44 percent return suggests a price reversal.

3.7.6 Abnormal Returns on Bonds in Which SIFIs Herded

We now examine whether the impact of herding on bond prices differs when the bonds are more heavily traded by SIFIs. It is worth noting that the Financial Stability Oversight Council (FSOC) has been criticized for designating some institutions as SIFIs without explaining the underlying process or factors that influence this designation (Wallison, 2014). If we find that SIFI insurers are associated with bond price impacts, then the evidence would lend credence to the argument that herding is one of the channels by which these insurers are systemically important.

We start by dividing the bond-quarter observations in two categories called SIFI and Non-SIFI, where the former includes all of the bonds for which insurers that are part of a group that is classified as a SIFI accounted for 15 percent or more of the total insurer trading volume in the bond during the quarter. The Non-SIFI Traded group consists of all of the other bonds. We also used a 25 percent cutoff to define the SIFI Traded group and found similar results.

We report results using the volume-based herding measure, but the results are similar if we use the LSV herding measure. Within each group, the bonds with non-missing buy herding measures are evenly divided into three portfolios. Portfolio BP3 consists of the bonds with the highest one-third buy herding measures and portfolio BP1 consists of the bonds with the lowest one-third buy herding measures. For both the SIFI and Non-SIFI groups, we examine the difference in the abnormal returns between BP3 and BP1. Similarly, the bonds with non-missing sell herding measures are evenly divided into three portfolios, with SP3 (SP1) being the portfolio with the highest (lowest) one-third sell herding measures. For both the SIFI and Non-SIFI groups, we examine the difference between the abnormal returns of SP3 and SP1.[42]

Table 3.13 reports the abnormal bond returns for high buy herding versus low buy herding (BP3-BP1) and for high sell herding versus low sell herding (SP3-SP1) for bonds with heavy trading by SIFIs versus bonds without heavy trading by SIFIs. The main result is that during the portfolio formation quarter, the high sell herding portfolio performs worse than the low sell herding portfolio when the bonds are heavily traded by SIFIs, as the difference in abnormal returns is -1.21 percent, which is statistically significant at the one percent level. In contrast, when the bonds are not heavily traded by SIFIs, the difference in abnormal returns is -0.35 percent and not significantly different from zero.

Thus, our evidence indicates that the prices of bonds in which herding takes place fall on average during the herding period when SIFI insurers are heavily involved in herding, but prices do not fall on average when other insurers herd. Stated differently, when herding impacts prices, SIFIs tend to be involved. If one of the objectives in identifying certain insurers as SIFIs was to identify insurers that can impact security prices, then it appears that the objective was achieved. Of course, impacting prices can be a good outcome if the

[42] We use six as opposed to the ten portfolios as we did in the analysis reported above to ensure a sufficient number of bonds in each portfolio given we have already split the sample in two groups based on whether the bonds were traded heavily by SIFIs.

SIFIs are impounding information into the bond's price. Our evidence suggests that this is the case, as the alternative interpretation that SIFIs are pushing the bond price below fundamental values is inconsistent with our findings of no rebound in the price in the subsequent quarter.

3.8 Summary and Implications for the Systemic Risk of Life Insurers

Using two different measures of investment herding (correlated trading) among institutions, we find that U.S. life insurers' investment decisions in corporate bonds are consistent with herding behavior. That is, on average life insurers tend to be on the same side of the market (either buying or selling) in individual corporate bonds than would be expected if their investment decisions were independent of each other. Sell side herding among insurers is more pronounced in smaller bonds, lower rated bonds, and bonds that have been downgraded. Herding is also more pronounced when insurers that are part of groups that have been designated as systemically important (SIFIs) trade the bonds.

Correlated trading among life insurers is one of the channels that has been put forth for why life insurers could contribute to systemic risk (see e.g., FSOC (2013), Getmansky et al. (2016) Paulson and Rosen (2016), and Schwarcz and Schwarcz, 2014). The evidence that insurers herd therefore lends credence to the argument that life insurers' investment activities could be a source of systemic risk. However, correlated trading does not imply that life insurers' investment decisions have a negative impact on market prices. Thus, we also examine the relationship between herding behavior and bond abnormal returns. We find that sell herding follows poor bond performance, which would suggest that sell side herding could potentially exacerbate price declines. However, based on abnormal returns during the quarter in which herding takes place and in the subsequent quarter, we find little evidence that insurer herding caused prices to move away from fundamental values during our sample period.

What are the implications of the results for the issue of whether insurers are systemically important, i.e., whether life insurers could potentially exacerbate a financial crisis? Before addressing this issue, it is important to highlight that our analysis and discussion only addresses one possible channel by which insurers could be systemically important – the investment herding channel. We believe that the evidence in this paper is mixed as to whether insurers' investment behavior has the potential to disrupt financial markets. On the affirmative side, we do find evidence of investment herding and evidence that sell side herding by insurers follows bond price declines. On the other hand, we find little evidence that this herding pushes prices away from fundamental values.

Table 3.1: Sample Selection Process

Life Insurer bond transactions are from Schedule D, Parts 3, 4, and 5 of life insurer annual statements. Following Rossi (2014), we delete observations with a 50% return reversal and if the absolute difference between the price and the median price over the prior 10 transactions and subsequent 10 transactions is "large." See footnote 16 for more details.

Step	Total Sample	Bond Transactions	Bond Issues	Bond Issuers	Insurance Companies
1	Life Insurer bond transactions from 2003-2011 after deleting obs. with no cusip, no transaction date, and non-secondary market trades	3,958,818	389,883	53,011	1,152
2	Delete non-secondary mkt trades	2,295,254	315,961	48,864	1,148
3	Merged with FISD and				
	Keep corporate bonds	968,162	27,033	6,540	988
	Delete foreign bonds	967,991	26,990	6,517	988
	Keep fixed coupon bonds	941,925	23,984	6,208	987
	Keep bonds w/ a credit rating	789,622	20,733	5,425	977
	Keep bonds w/ age > 3 qtrs	494,104	17,521	5,023	967
	Keep bonds w/ maturity > 2 qtrs	482,567	17,316	5,024	965
4	Merged with TRACE & delete transactions with likely errors in reported prices*	423,500	13,689	3,816	964
5	Merged with Insurer data & delete obs. with non-positive surplus, total assets, or premiums written	382,084	12,875	3,675	908
6	Require return in previous quarter	347,632	12,165	3,556	904
7	Require 5 transactions per quarter	176,541	5,752	2,088	904

Table 3.2: Characteristics of Bonds and Insurers in the Sample

Maturity is the number of years until the bond matures. Bond Age is the number of years that the bond has existed. Face amount is the face amount of the bond ($millions). Credit Rating is the average of the S&P, Moody's, and Fitch ratings and takes a value between 1 and 10 with 10 being AAA, 9 above AA, etc. Investment grade is equal to one if the bond is investment grade (rating above BB) and zero otherwise. Amihud Liquidity is the measure of liquidity in Amihud (2002) winsorized at the 1 and 99 percentile values. Prior quarter return is the abnormal return in the previous quarter winsorized at the 1 and 99 percentile values. The insurer characteristics are for the prior year and are volume-weighted averages of the variable for the insurers transacting in the bond in the quarter. #InsTrans = the number of insurers transacting in the bond during the quarter, PctVol_SIFI is the proportion of insurer volume in the bond from companies that are part of a group that has been designated as a SIFI. RBC is the risk-based capital ratio, winsorized at the 1 and 99 percentile values. Assets is total assets ($billions). LogAssets is the natural logarithm of total assets. I(Life Bus >75%) equals one if the percentage of premiums written from life insurance exceeds 75 percent and zero otherwise. I(Ann Bus > 75%) equals one if the percentage of premiums written from annuities exceeds 75 percent and zero otherwise. I(A&H Bus > 75%) equals one if the percentage of premiums written from accident and health insurance exceeds 75 percent and zero otherwise. Values are based on 20,760 bond-quarters.

Bond Characteristics	Var Name	Mean	Median	Min	Max	Stdev
Maturity when issued (yrs.)		13.9	10.0	2.0	100.0	9.1
Bond Age (yrs)	Age	4.1	3.3	1.0	24.3	2.7
Face Amount ($mill)		860.3	551.5	0.1	7,362.8	830.7
Ln(Face Amount) ($mill)	AmtOutst	13.3	13.2	3.9	15.8	0.8
Credit Rating	Rating	6.9	7.0	1.0	10.0	1.2
Investment Grade (%)	InvGr	72.6	100.0	0.0	100.0	44.6
Upgraded (in %)	UpGr	2.7	0.0	0.0	100.0	16.3
Downgraded (in %)	DownGr	7.2	0.0	0.0	100.0	25.9
Prior qtr Return (in %)	PrRet	-0.4	-0.2	-24.7	21.3	5.5
Amihud Liq. measure	Liquidity	0.7	0.4	0	5.0	0.8
Insurer Characteristics						
# of Insurers transacting	#InsTrans	7.8	7.0	5	72	3.8
Avg Risk-Based Capital Ratio	Avg RBC	8.4	8.1	5.2	20.0	2.2
Avg Return on Assets (in %)	Avg ROA	0.9	0.9	-33.3	28.0	2.1
Avg value of Assets ($billions)		43.8	32.3	0.1	237.0	37.5
Avg Log(Assets)	AvgLogAssets	23.5	23.6	17.7	26.2	1.0
% of volume by SIFIs	PctVol_SIFI	21.3	2.9	0.0	1.0	29.2
Avg I(Life Bus > 75%)	Avg Life_Foc	0.13	0.04	0.00	1.00	0.19
Avg I(Ann Bus > 75%)	Avg Ann_Foc	0.39	0.37	0.00	1.00	0.29
Avg I(A&H Bus > 75%)	Avg AH_Foc	0.09	0.01	0.00	1.00	0.15

Table 3.3: Credit Rating Distribution

Avg rating of 3 credit rating agencies	Credit Rating	% of Obs.
AAA	10	0.9%
Above AA	9	3.3%
Above A	8	26.1%
Above BBB	7	36.7%
Above BB	6	15.1%
Above B	5	11.6%
Above CCC	4	3.7%
Above CC	3	0.7%
Above C	2	0.3%
Default	1	0.2%
NR&w	w	0.9%

Table 3.4 Herding Measures

The overall herding measure, LSV_HM, is based on the absolute value of the difference between the proportion of insurers buying a particular bond relative to the proportion of insurers buying any bond during the quarter. The buy (sell)) herding measure, LSV_BHM (LSV_SHM), is the value of LSV_HM if the difference between the proportion of insurers buying the bond is greater (less) than the proportion of insurers buying any bond during a given quarter, and missing otherwise. The overall volume based herding measure, VOL_HM, is equal to the absolute value of the difference between insurers' buy volume and sell volume, divided by insurers' total volume. The buy (sell) herding measures based on volume, VOL_BHM (VOL_SHM) equal the value of VOL_HM if the buy volume of insurers is greater (less) than the sell volume of insurers in the bond during the quarter, and missing otherwise.

Panel A: Herding Measures for Sample of Insurers Transacting in Corporate Bonds from 2002 - 2011

Variable	N	Mean	StdDev
LSV_HM	20,760	10.2%	15.8%
LSV_BHM	10,204	11.1%	16.4%
LSV_SHM	10,556	9.4%	15.3%
VOL_HM	20,760	60.5%	33.6%
VOL_BHM	9,029	56.5%	33.3%
VOL_SHM	11,723	63.7%	33.5%

Panel B: Representative Results from the Literature on Institutional LSV Herding Measures

Reference	Institutions	Securities	Time Period	Mean HM	Mean BHM	Mean SHM
Lakonishok et al. (1992)	Pension funds	Stocks	'85-'89	2.7%		
	Pension funds	Small stocks	'85-'89	6.1%		
	Pension funds	Large stocks	'85-'89	1.6%		
Wermers (1999)	Mutual funds	Stocks	'75-'95	3.4%	2.9%	3.7%
	Mutual funds	Small stocks	'75-'95	6.2%	3.7%	8.1%
	Mutual funds	Large stocks	'75-'95	2.7%	2.5%	2.8%
Cai, et al. (2016)	Insurers	Corp bonds	'98-'14	13.2%	13.3%	12.5%
	Mutual funds	Corp bonds	'98-'14	9.6%	8.4%	10.8%
	Pension funds	Corp bonds	'98-'14	8.6%	9.0%	7.9%

Table 3.5: Panel Regressions for Herding Measures

Dependent variable is one of the six herding measures for bond i during quarter t described in Panel A of Table 3.4. The explanatory variables include the following characteristics of bond i during quarter t: Age = age in years. AmtOutst = logarithm of average amount outstanding. Rating = average rating score (1=default, 10==AAA); Rating1 is the first segment of a linear spline of Rating and Rating2 is the second segment. The knot for the spline is at seven, the threshold for an investment grade rating. Upgr = 1 if bond is upgraded at least once during quarter, and 0 otherwise; Downgr = 1 if the bond is downgraded at least once during quarter, and 0 otherwise; Liquidity = average Amihud liquidity measure. PrRet<0 is the first segment of a linear spline for the previous quarter's winsorized abnormal return for the bond and PrRet>0 is the second segment of the spline, where the knot for the spline is equal zero.
#InsTrans = the natural logarithm of the number of insurers transacting in the bond during the quarter, PctVol_SIFI = the proportion of insurer volume in the bond from companies that are part of a group that has been designated as a SIFI. The other insurer characteristics are weighted averages of the insurer characteristics, where the weight is the percentage of volume from the insurer. Avg RBC = winsorized average risk-based capital ratio; AvgRBC<7 (7≤Avg RBC<9) is a dichotomous variables that equals zero unless the Avg RBC ratio is less than 7 (between 7 and 9), in which case the variable equals one; Avg ROA = average return on assets; and Avg LogAssets = average logarithm of inflation adjusted general account assets; Avg Life_Foc, Avg Ann_Foc, and Avg AH_Foc, give the average value of the dichotomous variable indicating whether an insurer has 75% of its premium revenue from life, annuities, or accident & health insurance, respectively.
Coefficients are reported with robust standard errors in parentheses. Bond and quarter fixed effects are included in the regressions. ***, **, * indicate significance at the 0.01, 0.05, 0.10 level, respectively.

	LSV_HM	VOL_HM	LSV_BHM	VOL_BHM	LSV_SHM	VOL_SHM
Age	-0.034	0.073	-0.062	-0.121	0.014	0.274***
	(0.030)	(0.064)	(0.056)	(0.127)	(0.046)	(0.095)
AmtOutst	-0.045***	-0.096***	0.016	-0.017	-0.044***	-0.086***
	(0.008)	(0.016)	(0.031)	(0.083)	(0.010)	(0.016)
Liquidity	0.001	-0.002	-0.004	-0.014	0.005	0.004
	(0.002)	(0.005)	(0.005)	(0.010)	(0.004)	(0.007)
Rating1	-0.037***	-0.063***	-0.027*	0.027	-0.033***	-0.046***
	(0.004)	(0.008)	(0.014)	(0.029)	(0.005)	(0.009)
Rating2	-0.020***	-0.047***	-0.008	-0.070**	-0.011	-0.038***
	(0.007)	(0.016)	(0.015)	(0.036)	(0.012)	(0.023)
UpGr	0.006	0.043**	0.015	0.070**	-0.010	0.030
	(0.009)	(0.018)	(0.016)	(0.034)	(0.013)	(0.027)
DownGr	0.006	0.045***	-0.038**	-0.049	0.027***	0.051***
	(0.006)	(0.012)	(0.016)	(0.038)	(0.008)	(0.015)
PrRet<0	-0.017	-0.190*	-0.024	0.233	-0.136**	-0.433***
	(0.049)	(0.097)	(0.115)	(0.238)	(0.064)	(0.135)
PctVol_SIFI	0.018***	0.047***	0.038***	0.048*	0.013	0.039**
	(0.006)	(0.013)	(0.011)	(0.025)	(0.010)	(0.019)
# InsTrans	0.044***	-0.109***	0.038***	-0.144***	0.052***	-0.094***
	(0.004)	(0.009)	(0.008)	(0.017)	(0.007)	(0.013)
Avg RBC<7	0.015***	0.026***	0.016*	0.021	0.009	0.026*
	(0.005)	(0.010)	(0.009)	(0.019)	(0.007)	(0.015)
7≤Avg RBC<9	0.007*	0.009	0.004	0.004	0.006	0.010
	(0.004)	(0.008)	(0.007)	(0.016)	(0.006)	(0.012)
Avg ROA	-0.092	-0.168	-0.199	-0.612*	0.075	-0.005
	(0.091)	(0.184)	(0.167)	(0.364)	(0.141)	(0.265)
Avg LogAssets	-0.006***	0.012***	-0.013***	-0.002	-0.001	0.022***
	(0.002)	(0.004)	(0.003)	(0.007)	(0.003)	(0.006)
Avg Life_Foc	-0.000	0.026	0.004	0.055	0.002	0.029
	(0.009)	(0.019)	(0.016)	(0.036)	(0.014)	(0.027)
Avg Ann_Foc	0.001	0.039***	-0.007	0.053**	0.008	0.034*
	(0.006)	(0.013)	(0.011)	(0.024)	(0.010)	(0.018)
Avg AH_foc	0.013	0.013	0.019	0.009	0.013	0.012
	(0.012)	(0.026)	(0.021)	(0.051)	(0.019)	(0.037)
Constant	0.975**	2.105***	0.302	1.389	0.700***	1.413***
	(0.123)	(0.240)	(0.428)	(1.147)	(0.152)	(0.268)
R^2	0.38	0.38	0.50	0.52	0.55	0.52
N	20,760	20,760	10,204	9,029	10,556	11,723

Table 3.6: Impact of Consolidating Transactions of Insurers in the Same Group on Average Herding Measures

Transactions of insurers in the same group during the same quarter are consolidated to calculate the various herding measures. The overall herding measure, LSV_HM, is based on the absolute value of the difference between the proportion of insurers buying a particular bond relative to the proportion of insurers buying any bond during the quarter. The buy (sell)) herding measure, LSV_BHM (LSV_SHM), is the value of LSV_HM if the difference between the proportion of insurers buying the bond is greater (less) than the proportion of insurers buying any bond during a given quarter, and missing otherwise. The overall volume based herding measure, VOL_HM, is equal to the absolute value of the difference between insurers' buy volume and sell volume, divided by insurers' total volume. The buy (sell) herding measures based on volume, VOL_BHM (VOL_SHM) is the value of VOL_HM if the buy volume of insurers is greater (less) than the sell volume of insurers in the bond during the quarter, and missing otherwise.

Variable	N	Mean	StdDev
LSV_HM	12,042	5.7%	14.6%
LSV_BHM	6,039	6.0%	14.6%
LSV_SHM	6,003	5.5%	14.5%
VOL_HM	12,042	56.4%	32.3%
VOL_BHM	5,2673	52.6%	31.4%
VOL_SHM	6,775	59.4%	32.7%

Table 3.7: Abnormal Returns Based on Transaction Prices for Portfolios Formed Based on LSV Herding Measures

Average abnormal returns for 10 portfolios formed in each of 36 quarters from the 1st quarter of 2003 through 2011. B1_LSV (B5_LSV) consists of bonds with the lowest (highest) LSV buy herding measures during each quarter and S1_LSV (S5_LSV) consists of bonds with lowest (highest) LSV sell herding measures during each quarter. Abnormal returns are calculated using 34 benchmark portfolios as described in the text and winsorized at the 1% and 99% values. Statistical significance is based on a sign rank test of standardized abnormal returns.

			Average Abnormal Returns		
Buy Herding Portfs	Avg # of bonds	Average BHM	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
B1_LSV	55	-9.7%	0.01%	0.03%	-0.40% **
B2_LSV	57	-0.1%	-0.12%	-0.08%	-0.25% *
B3_LSV	57	10.0%	-0.19% *	-0.08%	-0.26%
B4_LSV	56	20.9%	-0.28%	0.13%	-0.10%
B5_LSV	55	36.2%	-0.18%	0.17%	-0.06%
B5_LSV – B1_LSV			-0.20%	0.14%	0.34%
B4_LSV – B1_LSV			-0.29%	0.10%	0.30% **

			Average Abnormal Returns		
Sell Herding Portfs	Avg # of bonds	Average SHM	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
S1_LSV	57	-11.1%	-0.03%	-0.34% *	-0.28% *
S2_LSV	59	-1.1%	-0.32% ***	-0.46% **	-0.31% **
S3_LSV	57	8.9%	-0.68% ***	-0.66% **	-0.53% ***
S4_LSV	56	20.7%	-0.61% ***	-1.12% ***	-0.28%
S5_LSV	52	29.8%	-1.41% ***	-1.14% ***	-0.71% **
S5_LSV - S1_LSV			-1.39% ***	-0.80%	-0.43%
S4_LSV - S1_LSV			-0.59% *	-0.78%	0.00%

Table 3.8: Abnormal Returns Based on Transaction Prices for Portfolios formed using Herding Measures Based on Insurer Volume

Average abnormal returns for 10 portfolios formed in each of 36 quarters from 2003 through 2011. B1_VOL (B5_VOL) consists of bonds with the lowest (highest) volume based buy herding measures during each quarter and S1_VOL (S5_VOL) consists of bonds with lowest (highest) volume based sell herding measures during each quarter. Abnormal returns are calculated using 34 benchmark portfolios as described in the text and winsorized at the 1% and 99% values. Statistical significance is based on a sign rank test of standardized abnormal returns.

			Average Abnormal Returns		
	Avg #	Average		Portfolio	
Buy Herding Portfs	bonds	BHM	Qtr Prior	Frmtn Qtr	Qtr After
B1_VOL	49	10.7%	-0.13%	-0.20% **	-0.28%
B2_VOL	50	32.9%	-0.28% *	0.16%	-0.20%
B3_VOL	50	57.5%	-0.21%	0.01%	-0.17% *
B4_VOL	48	83.0%	-0.28% *	0.15%	-0.17%
B5_VOL	51	99.1%	-0.12%	0.13%	-0.05%
B5_VOL – B1_VOL			0.01%	0.33% **	0.22%
B4_VOL – B1_VOL			-0.14%	0.35% *	0.11%

			Average Abnormal Returns		
	Avg #	Average		Portfolio	
Sell Herding Portfs	bonds	SHM	Qtr Prior	Frmtn Qtr	Qtr After
S1_VOL	64	13.7%	-0.05%	-0.20% **	-0.42% ***
S2_VOL	64	42.4%	-0.15% **	-0.59% ***	-0.16%
S3_VOL	64	70.5%	-0.43% ***	-0.71% ***	-0.39% *
S4_VOL	52	91.7%	-0.70% ***	-0.64% ***	-0.48% ***
S5_VOL	69	99.8%	-1.09% ***	-1.03% ***	-0.62% ***
S5_VOL – S1_VOL			-1.05% **	-0.83% *	-0.19%
S4_VOL – S1_VOL			-0.65% ***	-0.44%	-0.06%

Table 3.9: Abnormal Returns Based on Quoted Prices

Average abnormal returns for 10 portfolios formed in each of 36 quarters from 2003 through 2011. B1_LSV (B5_LSV) consists of bonds with the lowest (highest) LSV buy herding measures during each quarter and S1_LSV (S5_LSV)) consists of bonds with lowest (highest) LSV sell herding measures during each quarter. Portfolios based on the volume based herding measures are defined similarly. Abnormal returns are calculated using the Citi US Broad Investment Grade Bond Index and Citi High Yield Market Index. This approach allows us to classify bonds into five major rating categories (AAA, AA, A, BBB, BB,B, CCC), and then segment these categories into intermediate and long-term indices based upon time to maturity, resulting in 28 matching portfolios. For investment grade bonds, the time to maturity categories are 1 to 3 years, 3 to 7 years, 7 to 10 years, and 10 or more years. For non-investment grade bonds, the categories are 1 to 7 years, 7 to 10 years, and 10 or more years. The abnormal returns are winsorized at the 1% and 99% values. Statistical significance is based on a sign rank test of standardized abnormal returns.

Panel A: LSV Buy Herding	Average Abnormal Returns		
	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
B5_LSV – B1_LSV	0.15%	0.66% **	-0.01%
B4_LSV – B1_LSV	-0.16%	0.51% **	0.13%

Panel B: LSV Sell Herding	Average Abnormal Returns		
	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
S5_LSV - S1_LSV	-0.64% **	-0.45%	0.21%
S4_LSV - S1_LSV	-0.38% ***	-0.11%	-0.12%

Panel C: VOL Buy Herding	Average Abnormal Returns		
	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
B5_VOL – B1_VOL	0.09%	0.38%	-0.12%
B4_VOL – B1_VOL	-0.19%	0.31%	0.10%

Panel D: VOL Sell Herding	Average Abnormal Returns		
	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
S5_VOL - S1_VOL	-0.66% *	-0.42% *	0.09%
S4_VOL - S1_VOL	-0.19%	-0.42% *	0.04%

Table 3.10: Abnormal Returns Based on Raw Returns

Average returns for 10 portfolios formed in each of 36 quarters from 2003 through 2011. B1_VOL (B5_VOL) consists of bonds with the lowest (highest) volume based buy herding measures during each quarter and S1_VOL (S5_VOL) consists of bonds with lowest (highest) volume based sell herding measures during each quarter. Returns are winsorized at the 1% and 99% values. Statistical significance is based on a sign rank test of standardized returns.

Panel A: LSV Buy Herding	Average Returns		
	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
B5_LSV – B1_LSV	-0.20%	0.01% *	0.37%
B4_LSV – B1_LSV	-0.12%	0.03%	0.32%

Panel B: LSV Sell Herding	Average Returns		
	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
S5_LSV - S1_LSV	-0.80% ***	0.08% **	0.92%
S4_LSV - S1_LSV	-0.40% *	-0.25% ***	0.54%*

Panel C: VOL Buy Herding	Average Returns		
	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
B5_VOL – B1_VOL	0.19%	0.36% **	0.35%
B4_VOL – B1_VOL	-0.12%	0.19% **	0.29

Panel D: VOL Sell Herding	Average Returns		
	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
S5_VOL - S1_VOL	-0.51% **	0.07% **	1.06%
S4_VOL - S1_VOL	-0.33%	0.15%	0.61%

Table 3.11: Insurer Bond Purchases following Sales in the Prior Quarter

Portfolios S1 through S5 are formed based on either the LSV sell herding measures (Panel A) or the Volume based sell herding measures (Panel B) with S1 having the lowest sell herding and S5 the highest sell herding. The percentage of bonds in the portfolio that are sold in the portfolio formation quarter and then purchased in the subsequent quarter is calculated for each of the 36 quarters from 2003-2011. The second column reports the average across the quarters.

Panel A: LSV Sell Herding measures

Portfolio	Average % of Bonds in the Portfolio that are purchased in the subsequent quarter by the same insurers that sold the bonds during the portfolio formation quarter
S1_LSV	6.7%
S2_LSV	5.8%
S3_LSV	4.6%
S4_LSV	3.3%
S5_LSV	1.7%

Panel B: Volume Sell Herding measures

Portfolio	Average % of Bonds in the Portfolio that are purchased in the subsequent quarter by the same insurers that sold the bonds during the portfolio formation quarter
S1_VOL	8.4%
S2_VOL	7.3%
S3_VOL	5.0%
S4_VOL	3.7%
S5_VOL	1.7%

Table 3.12: Abnormal Returns on Portfolios formed Based on Herding Measures for Different Time Periods

Average abnormal returns for the difference between portfolios formed in each of 36 quarters from 2003 through 2011. B1 (B5) consists of bonds with the highest (lowest) buy herding measures during each quarter and S5 (S1) consists of bonds with highest (lowest) sell herding measures during each quarter. Panel A use the LSV herding measures and Panel B uses the Volume based herding measures. Abnormal returns are calculated using 34 benchmark portfolios as described in the text. Statistical significance is based on a sign rank test of standardized abnormal returns.

Panel A: Average Abnormal Returns on Portfolios formed using LSV Herding Measures

	Prior to the Fin Crisis ('03-'07)			**During the Fin Crisis** ('08-'09)			After the Fin Crisis ('10-'11)		
	Qtr Prior	Herding Qtr	Qtr After	Qtr Prior	Herding Qtr	Qtr After	Qtr Prior	Herding Qtr	Qtr After
Buy Portf									
B5 – P1	-0.05%	0.23%	0.06%	-0.47%	0.51%	0.66%	-0.27%	-0.39%	0.69%
B4 – P1	0.03%	0.18%	0.09%	-1.13%	-0.16%	0.72%	-0.41%	0.21%	0.67%
Sell Portf									
S5 – S1	-0.81%*	-0.98%**	-0.41%	-3.77%**	1.24%	-0.90%	-1.04%	-0.63%	-0.04%
S4 – S1	-0.30%	-0.36%	-0.19%	-1.84%	-0.93%	1.44%	-0.53%	-1.12%	-0.21%

Panel B: Average Abnormal Returns on Portfolios formed using Volume Based Herding Measures

	Prior to the Fin Crisis ('03-'07)			**During the Fin Crisis** ('08-'09)			After the Fin Crisis ('10-'11)		
	Qtr Prior	Herding Qtr	Qtr After	Qtr Prior	Herding Qtr	Qtr After	Qtr Prior	Herding Qtr	Qtr After
Buy Portf									
B5 – B1	0.02%	0.19%	0.07%	0.17%	0.98%	0.03%	-0.02%	0.22%	0.75%
B4 – B1	0.03%	0.11%	0.02%	-0.60%	1.22%	0.00%	-0.13%	0.30%	0.45%
Sell Portf									
S5 – S1	-0.54%	-0.86%**	-0.17%	-2.58%	-0.29%	-0.02%	-1.31% **	-0.22%	0.07%
S4 – S1	-0.32%	-0.22%	-0.12%	-1.28%	-0.25%	0.34%	-1.16% **	-1.15%	0.04%

Table 3.13: Abnormal Returns on Bonds in Which SIFIs Herded

Bonds in the SIFI Group consist of bonds in which at least 15% of the trading volume in the bond during quarter was from insurers that were part of a group that is now classified as a SIFI. All other bonds are in the Non-SIFI Group. Within the SIFI and Non-SIFI Groups, bonds with non-missing buy herding measures based on volume are placed into three portfolios based on their buy herding measures, with BP3 (BP1) being the portfolio with the largest (smallest) buy herding measures based on volume, and SP3 (SP1) is the portfolio with the largest (smallest) sell herding measures based on volume.

	Group	Qtr Prior	Portfolio Frmtn Qtr	Qtr After
Buy Portf				
BP3 – BP1	SIFI	-0.17%	0.18%	0.13%*
BP3 – BP1	Non-SIFI	0.01%	0.14%	0.11%
Sell Portf				
SP3 – SP1	SIFI	-0.77%	-1.21%***	-0.67%
SP3 – SP1	Non-SIFI	-0.89%**	-0.35%	-0.00%

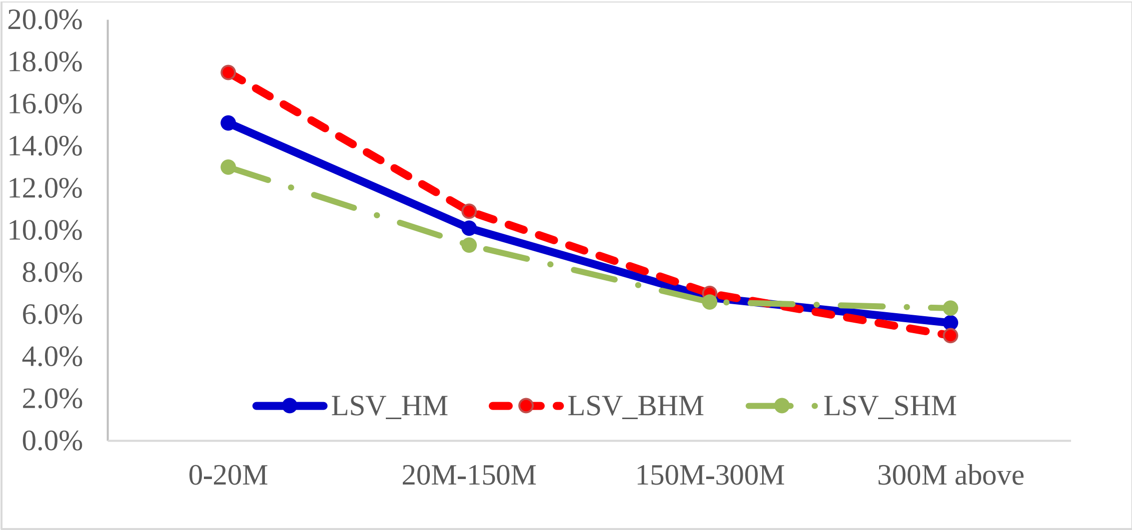

Figure 3.1: LSV Herding Measures by Bond Size (Amount Outstanding)

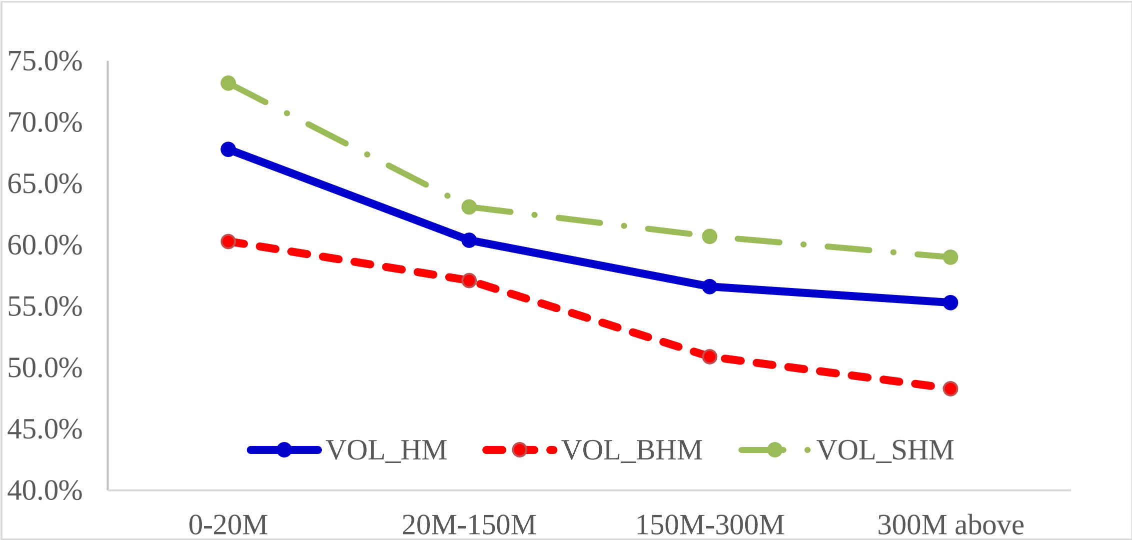

Figure 3.2: Volume based Herding Measures by Bond Size (Amount Outstanding)

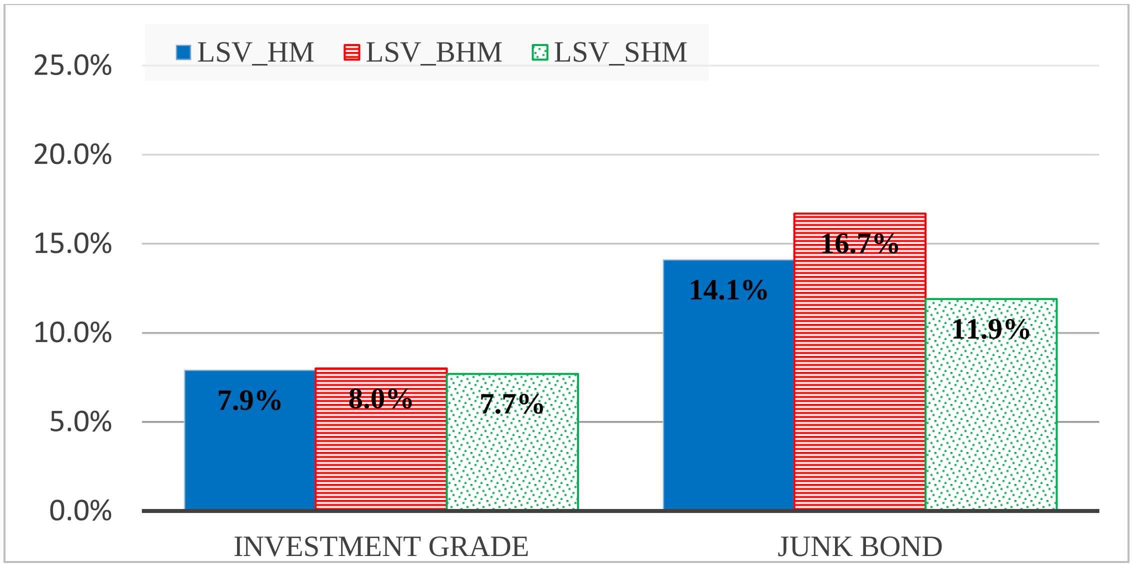

Figure 3.3 LSV Herding Measures for Investment Grade versus Non-Investment Grade Bonds

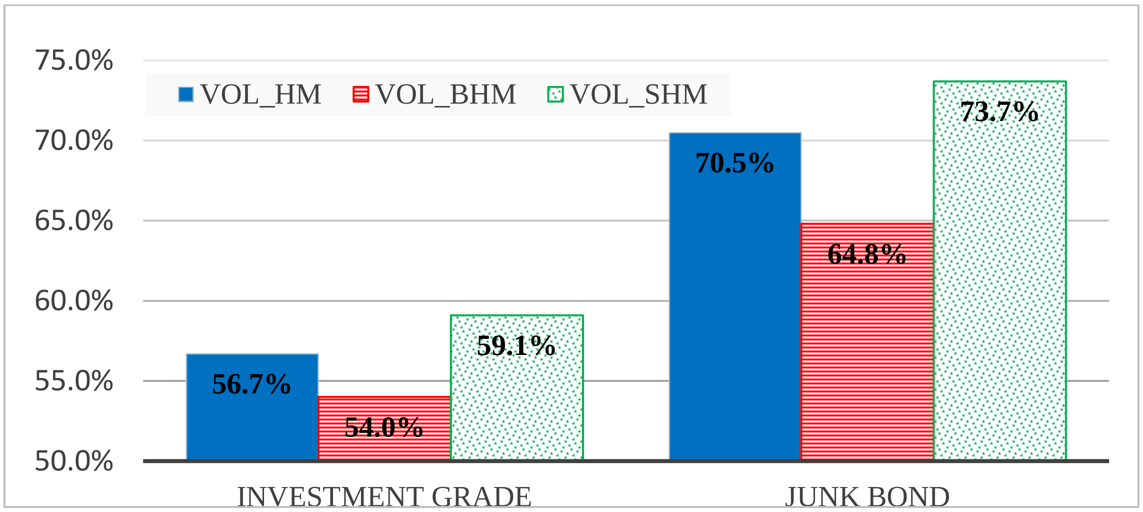

Figure 3.4 Volume-based Herding Measures for Investment Grade versus Non-Investment Grade Bonds

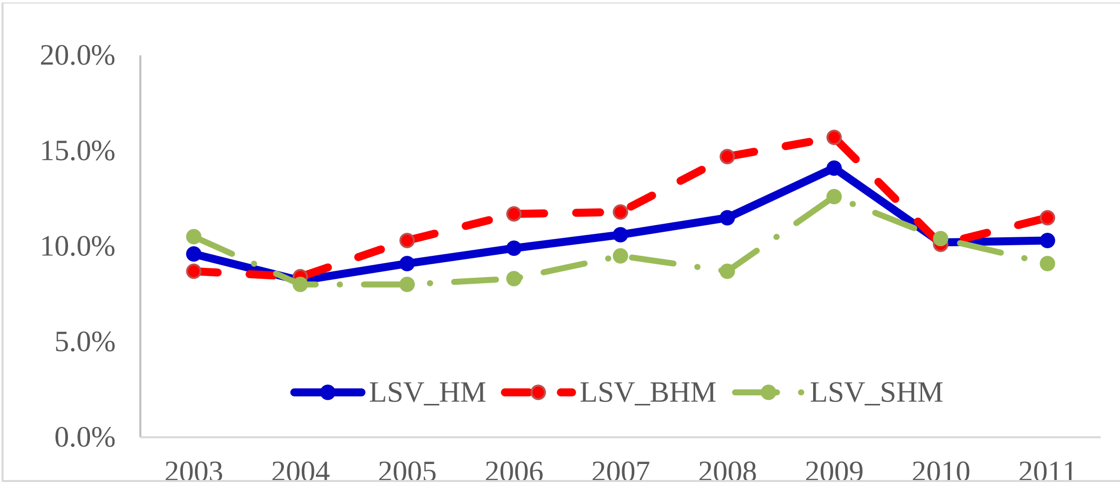

Figure 3.5 LSV Herding Measures by Year

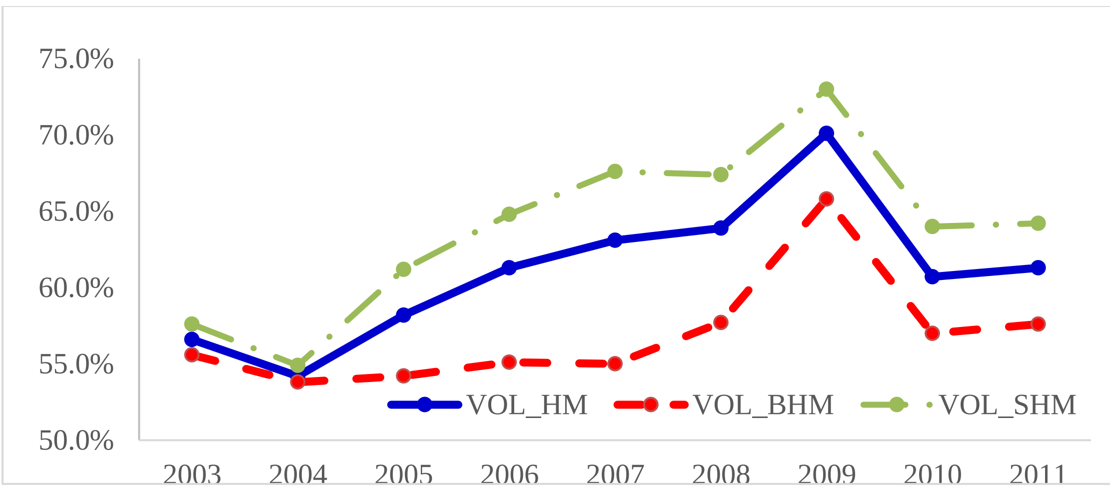

Figure 3.6 Volume-based Herding Measures by Year

CHAPTER 4

EFFECTS OF RELATIONSHIPS ON EXECUTION COSTS IN THE U.S. CORPORATE BOND MARKET[43]

4.1 Introduction

From a conceptual point of view, a relationship transaction can be distinguished from a pure spot market transaction by whether the terms of trade are influenced by either previous or anticipated future transactions between the parties.[44] Financial research has examined the role of relationships in a variety of settings, including between borrowers and lenders (e.g., Berger and Udell, 1992, Barath et al., 2009, and Bolton et al., 2016)), venture capital providers and subsequent borrowers (Hellman et al., 2008), and more recently between bond dealers and their customers (see cites below). This paper contributes to our understanding of the role of relationships between bond dealers and their customers by examining the interaction effects between relationships and the customer's market power in the relationship, which is measured by the size of the customer's dealer network, its expected future trading activity, and whether it has outsourced investment management services to an affiliate of the dealer.

Three recent papers examine execution costs in the corporate bond market and provide evidence on the role of relationships in this market. Di Maggio et al. (2017)

[43] Chia-Chun Chiang and Greg Niehaus. To be submitted to Journal of Risk and Insurance.
[44] There is an extensive literature in on how incomplete contracts, information problems, and transaction costs influence the governance of transactions, including the role of relationships. Seminal contributions include Coase (1937), Williamson (1979), and Grossman Hart (1986).

document that corporate bond market dealers charge lower spreads to those with whom the dealer has a stronger previous trading relationship and that the impact of a previous trading relationship on execution costs is greater in turbulent markets. Hendershott et al. (2015), who examine execution costs incurred by insurers, summarize their findings with "trading relations are the most important determinant of good execution terms." Their evidence is consistent with insurers developing a network (a Rolodex) of dealers, with the size of the network determined by the costs of initiating and maintaining a trading relationship and the benefits of having more potential competition. O'Hara et al. (2016) show that execution costs are on average greater for insurers with smaller bond portfolios, but that the greater execution costs paid by insurers with smaller bond portfolios is reduced on average when those insurers concentrate their trades with a relatively small set of dealers, presumably dealers with whom they had a prior trading relationship.

We build on these contributions by examining two related issues. First, does the impact of a previous trading relationships (shown to be important by De Maggio et al.) interact with the size of the insurer's dealer network (shown to be important by Hendershott et al.) and/or with the size of the insurer's bond portfolio (shown to be important by O'Hara et al.)? The interaction effects are motivated, in part, by the theoretical model of Bernhardt et al. (2005), in which the impact of a relationship on execution costs depends on the customer's bargaining power (network size is our proxy) and the customer's expected future order flow (bond portfolio size is our proxy). We hypothesize that an insurer with either a larger dealer network or a larger bond portfolio has greater market power in their dealer relationships. The interaction effects are therefore also motivated by the possibility that a strong prior trading relationship with a dealer (think of a customer that always uses the same dealer) could indicate that the dealer has monopoly power (see Sharpe, 1990), unless it is offset by the customer's market power, i.e., unless the customer has a large dealer network and/or a large bond portfolio.

The second question addressed is: does the impact of relationships on execution costs depend on whether the customer has other business with entities that are affiliated with the dealer? The specific type of other business that we examine is the outsourcing of investment management services to an affiliate of the dealer. As an example of this situation, an insurer could outsource some of its asset management to Merrill Lynch and trade bonds with Bank of America. Since Merrill Lynch and Bank of America are part of the same organization after 2008, we classify such an insurer as having a cross-relationship with Bank of America. While the banking literature contains a number of studies examining whether transactions with one part of a financial institution influence transactions terms with another part of the institution (Yasuda, 2005; Drucker and Puri, 2005; Hellmann et al., 2008), this issue has not to our knowledge been examined in the dealer market for corporate bonds. We hypothesize that outsourcing of investment management services with an affiliate of a dealer strengthens a customer's market power in its bond trading relationship with the dealer.

We use NAIC life insurer transaction data from 2003 to 2011. Consistent with De Maggio et al. (2017), we define a relationship trade at a given point in time by whether the customer and counterparty involved in the trade transacted in the past quarter. We measure the strength of the relationship between an insurer and the counterparty by the proportion of the insurer's bond trading in the previous quarter that was with the same counterparty. Thus, if an insurer trades with three dealers in the previous quarter, we classify the insurer as having a relationship with each of those dealers. If one-half of the insurer's volume of trading in the prior quarter was with one dealer and the other half split between the other two dealers, then the insurer has a stronger relationship with the former than with the latter dealers.

Our analysis controls for a number of factors that theoretically are related to transacting costs in securities markets, including the dealers' inventory costs, information asymmetry about the underlying security being traded, and search-and-bargaining costs (see e.g., Amihud and Mendelson, 1980, Glosten and Milgrom, 1985, Kyle, 1985, Duffie et al., 2005; Rhodes-Kropf, 2005; Bernhardt et al., 2005). Consistent with the theory, existing empirical evidence finds that trade size, bond liquidity, dealer size, and transparency influence bond execution costs (see e.g., Schultz, 2001; Bessembinder et al., 2006; Edwards et al., 2007).

Our evidence confirms that trading relationships influence bond execution costs. While Di Maggio et al. (2017) find a negative association between execution costs and stronger trading relationships on average, we find a positive association on average for our entire sample. However, we also find that the association between prior trading relationships and execution costs is conditional on the size of the insurer's dealer network and on the size of the insurer's bond portfolio. More specifically, holding the strength of the relationship constant, insurers with smaller dealer networks and smaller bond portfolios suffer higher execution costs than insurers with larger networks and larger bond portfolios, all else equal. This evidence suggests that when insurers with a limited dealer network and/or relatively small bond portfolios have a strong trading relationship with particular dealers, the dealers have some monopoly power and charge higher execution costs. This does not imply that insurers are not optimizing, as the higher execution costs that they pay may be lower than the costs of establishing and maintaining additional relationships. In addition, we find that outsourcing of investment services to an affiliate of a dealer lowers bond execution costs for customers that otherwise would have weak market power when they trade with a relationship dealer. Thus, our paper augments the Di Maggio et al. (2017)'s paper and those by Hendershott et al. (2015) and O'Hara et al. (2016) by presenting evidence that the impact of relationships on execution costs varies with the size of the insurer's dealer network, the size of the insurer's bond portfolio, and whether the insurer outsources some of its asset management services to an affiliate of the counterparty, i.e, whether a cross-relationship exists.

In most of our analysis, we treat the existence of a relationship as exogenous, which is clearly not the case. Customers choose which dealers to trade with and how many to trade with. In an effort to address the endogeneity issues, we conduct a propensity score matching analysis. The results are consistent with the regression analysis, i.e., the impact of relationship trades on execution costs depends on whether the customer has strong or weak market power. Customers with strong market power enjoy lower execution costs in relationship trades compared to those with weak market power.

The paper proceeds as follows. In section 4.2, we present the hypotheses to be tested. The data are described in section 4.3. The methodology and a descriptive analysis of the data are presented in section 4.4, followed by the results. The final section summarizes and offers some conclusions.

4.2 Existing Literature and Hypotheses

4.2.1 The Setting

Our hypotheses are about how relationships between participants in the secondary corporate bond market influence execution costs. In our case, a life insurer is on one side of the transaction. Typically, a dealer is the counterparty, but not always. Our analysis is at the level of individual bond transactions, which are defined by the insurance company (indexed by i) and the counterparty (indexed by d) involved in the transaction, the bond that is being traded (indexed by b), and the date of the transaction (indexed by t). We have data on insurer characteristics and bond characteristics, but not counterparty characteristics.[45] Therefore, our hypotheses regarding relationships relate execution costs to insurer characteristics, controlling for bond characteristics.

4.2.2 Prior Literature

There are several theoretical models in the literature that highlight different factors that are likely to influence bond execution costs. Dealers have costs of holding inventory, which imply that bonds that trade infrequently and transactions that would cause an inventory imbalance (e.g., large trades) will have higher execution costs, all else equal (see e.g., Amihud and Mendelson, 1980; Bernhardt et al., 2005, Also, if customers are better informed about the value of the underlying bonds, then the counterparty will charge higher execution costs, all else equal (see e.g., Glosten and Milgrom, 1985 and Kyle, 1985). Assuming asymmetric information is more prevalent with smaller and lower rated bonds, execution costs would be higher for such bonds (Edwards, et al, 2007).

[45] Hendershott et al. (2016) provide extensive analysis of dealer – insurer relations, including the influence of dealer characteristics.

Duffie et al. (2005) highlight the importance of customer search and bilateral bargaining between the customer and dealer in over-the-counter markets like the corporate bond market. They show that the execution cost on a given transaction depends on the customer's cost of finding an alternative dealer and the relative bargaining power of the customer versus the dealer. In essence, contemporaneous competition determines execution costs. Thus, the size of the customer's dealer network, defined as the number of dealers used in the prior quarter, is expected to be inversely related to execution costs. Hendershott et al. (2015) and O'Hara et al. (2016) provide evidence consistent with this prediction. Schultz (2001) presents evidence that execution costs in the corporate bond market are larger when smaller institutional investors trade and Hendershott et al. (2015) and O'Hara et al. (2016) show that smaller insurers on average pay higher execution costs. Assuming customer size is inversely related to search costs and directly related to bargaining power, these findings are consistent with Duffie et al.'s model. O'Hara et al. (2016) also show that the dealer's market share in a given bond has a large influence on average execution costs, consistent with a dealer's market power/bargaining power playing a role in determining execution costs (Duffie et al.,2005).

4.2.3 Hypotheses Regarding Relationships

In developing our hypotheses, we rely heavily on Bernhardt et al.'s (2005) model of relationships between a customer and a dealer. In their model, the customer would like to trade, over its lifetime, at the best prices possible. The customer continues to use a particular dealer – one with which it has a relationship – until either (1) a random exogenous event with a known probability of occurrence causes the customer to switch to another dealer or (2) the customer switches because the endogenous execution costs charged by the dealer is viewed as too high. The dealer chooses the execution costs on a given transaction to maximize its value, which trades off the additional profits from charging higher execution costs on the current transaction with the increased probability of losing future profits on the customers' future order flow. The competitive force that disciplines the dealer from charging high execution costs is the loss of future business, which Bernhardt et al. (2005) refer to as intertemporal competition. Thus, one prediction is that dealers charge lower execution costs to customers that have a higher expected future order flow, all else equal. Note, however, fixing the value of a particular relationship, the larger the current order, the greater is the incentive to charge higher execution costs on the current trade, because the dealer would receive a higher mark-up on the current trade.

From an empirical perspective, we define a transaction as a "*relationship trade*" if the insurer and counterparty involved in the transaction traded with each other in the prior calendar quarter.[46] In addition, we measure the *strength of a relationship* between an insurer and a counterparty for a particular transaction by the proportion of the insurer's trades (or the proportion of the insurer's volume of trading) in the prior quarter that was with the same counterparty. Di Maggio et al. (2017) use similar measures.

The first question is how do execution costs change as the strength of the relationship between an insurer and a counterparty increases? Assuming that a strong prior trading relationship is a reflection of the dealer providing low cost execution in the past, then one would expect that a strong prior trading relationship would be associated with low cost execution. Consistent with this logic, Di Maggio et al. (2017) present evidence that the stronger the relationship, the lower are execution costs, all else equal. It is also plausible, however, that a strong prior relationship could have the opposite effect on

[46] In robustness checks, we examine alternative prior time periods.

execution costs. The relationship strength measures are essentially the counterparty's market share of the insurer's prior bond trading business. A high market share could indicate that the insurer is "locked in" to the counterparty for some reason, which could be due to the costs of finding other counterparties, or a lack of incentive to search for other counterparties due to agency costs, or an information advantage that the relationship counterparty has obtained by trading with the insurer over time.[47] In essence, a strong relationship (i.e., high market share) could indicate that the counterparty does not need to be concerned with losing the customer's future business and therefore the counterparty exercises this monopoly power by increasing execution costs. Given the competing arguments for the impact of a strong relationship on execution costs, we have the following two hypotheses:

Hypothesis 1.a: On average, prior trading relationships between the dealer and the customer decrease current execution costs.

Hypothesis 1.b: On average, prior trading relationships between the dealer and the customer increase current execution costs.

Our main hypotheses are based on Bernhardt et al.'s (2005) prediction that a prior trading relationship lowers execution costs more as the insurer's expected future order flow increases and as the insurer's bargaining power increases. We use the size of the insurer's bond portfolio as a proxy for expected future order flow and the size of the insurer's dealer network as a proxy for its bargaining power.[48] In our subsequent discussion, we sometimes

[47] Sharpe (1990) uses the information advantage that arises from lending to a customer over time in analyzing the market power of banks in relationship lending. If a dealer obtains an information advantage by trading with an insurer over time, then in equilibrium, the pricing of trades at the beginning of the relationship would be lower. See Sharpe (1990).

[48] We present empirical results using the size of the insurer's bond portfolio. However, we have also used measures of the insurer's volume of trading and find similar results.

group these two effects together as one, and refer to them as the customer's market power. This leads to hypotheses two and three:

Hypothesis 2: All else equal, for a given level of trading relationship strength, execution costs decline as the size of the customer's bond portfolio increases.

Hypothesis 3: All else equal, for a given level of trading relationship strength, execution costs decline with the size of the insurer's counterparty network.

As mentioned above, Hendershott et al. (2015) show that an insurer's asset size is negatively related to execution costs, but they do not interact asset size with a measure of the strength of the prior trading relationship. Similarly, Hendershott et al. (2015) and O'Hara et al. (2016) present evidence that execution costs decline as the insurer's network increases, but they do not interact newwork size with a measure of the strength of the prior trading relationship.

We also contribute to the literature by examining an issue that has received considerable attention in the banking literature, i.e., whether transactions with one part of a financial institution influence the terms of transactions with another part of the institution (Yasuda, 2005; Drucker and Puri, 2005; Hellmann et al., 2008). Thus, we examine whether execution costs in the bond market depend on whether the customer has relationships with another entity that is part of the same financial institution as the counterparty in the bond transaction. More specifically, if an insurer outsources some of its investment management to an entity that is affiliated with a counterparty with which the insurer transacts, then we say that the insurer has a cross-relationship with the counterparty. We investigate whether such a cross-relationship influences execution costs, which leads to the following hypotheses:

Hypothesis 4: Outsourcing of investment management services to an affiliate of the dealer lowers execution costs, all else equal.

Hypothesis 5: All else equal, for a given level of trading relationship strength, execution costs decline when the insurer outsources investment management services to an affiliate of the counterparty.

4.3 Data

We collect the data from multiple sources from 2003 to 2011. Life insurer transaction data are from Schedule D, Parts 3, 4, and 5 of insurers' annual statements, which report information on bonds that the insurer purchased during the year (Part 3), sold during the year (Part 4), and bought and sold during the year (Part 5). After deleting those observations without a reported cusip, a par value or a transaction date, there are close to 3.5 million bond transactions reported by 1,147 different life insurance companies in 368,140 different bonds.

After merging with the Fixed Investment Securities Database (FISD), which provides bond characteristics, issuer characteristics, and rating history, we have a sample of 1.04 million trades. We only consider corporate bonds. In addition, to avoid the newly issued and maturing bonds issues, we keep bonds that have a remaining maturity greater than two-quarters and were issued at least three quarters prior. The number of bonds in the sample drops to 0.53 million as a result of this step. We only consider corporate US dollar bonds and bonds with a face value equal to $1,000, so that the bonds in the sample are comparable (O'Hara et al., 2016). We also drop non-secondary market trades, e.g., those categorized as exchange, call, or mature. Trades with multiple dealers or without dealers' names are deleted. The number of bonds decreases to 0.34 million after the above-mentioned criteria. Finally, we only consider trades by life insurers with normal status indicated by NAIC, which reduces the sample to 0.33 million trades.

Life insurers report their transaction amount (Consideration) and par value for each trade in Schedule D. The traded price is defined as the Consideration divided by par value. However, some life insurers have different units for Consideration and Par Value. To make sure the reasonability of the prices, we compare the prices reported in the Trade Reporting and Compliance Engine (TRACE). We follow Bessembinder, et al. (2009) and Dick-Nielsen (2014) to exclude canceled trades, corrected trades, reversal trades, and commission trades. We also follow Rossi (2014) deleting price errors. In addition, we only include securities that are traded at least two times in the same direction in the same day. If the ratio of trade price to Trace price is not between 0.75 and 1.25, we delete the transaction from our sample. We also eliminate trades with unrecognized dealers' names (vague abbreviation). Dealers that are part of the same group are considered as one entity. We have about 0.10 million trades in the end. Table 4.1 illustrates the details for constructing our sample. In the following analysis, we use these trades to examine the impacts of relationships on execution costs. When fixed effects are used, we delete singleton observations.

4.4 Analysis

4.4.1 Measuring Execution Costs

Our level of analysis is a trade made by an insurer i with a dealer d for bond b on day t. We measure execution costs on a given trade by comparing the trade price with the volume weighted average TRACE price for that bond on that day:

$$\text{Execution cost}_{i,d,b,t} = \frac{TRACE\ average\ price_{b,t} - Trade\ Price_{i,d,b,t}}{TRACE\ average\ price_{b,t}} \times (1 - 2 \times 1_{buy\ (i,d,b,t)}), \qquad (1)$$

where 1_{buy} is an indicator of whether the trade is a buy or sell trade.

Our measurement of the execution costs is similar to those used in other studies, but not identical. Hendershott et al. (2016) compare the trade price to the Bank of America Merrill Lynch sell quotes at the time of the transaction for the same bond. Di Maggio et al. (2017) use two execution cost measures. For the one cost measure, they limit their analysis to bonds for which the dealer purchased and sold the bond in the same hour. For these bonds, the execution cost is the difference between the buy and the sell price. To increase the size of the sample and avoid limiting their sample to bonds with high liquidity, they expand the sample and use the difference between the transaction price and the average transaction price for that bond during the week. O'Hara et al. (2016) focus on the difference in transaction prices for the same bond traded on the same day in the same size category for insurers with large bond portfolios versus insurers with small bond portfolios.

4.4.2 Methodology and Baseline Model

We begin the analysis by examining the impact of relationships on execution costs for our sample. Recall, Di Maggio et al. (2017) find that execution costs are lower when the dealer and customer have a stronger prior trading relationship. Our first step therefore is to examine whether similar results hold in our sample. As we show shortly, we find different results on average. This could be explained, in part, by the different samples: We consider the execution costs of insurers; whereas, Di Maggio et al. (2017) use a broader set of transactions, including dealer to dealer trades. In the subsequent analysis, we interact the relationship variables with other factors to help explain why on average we find different results. Thus, we estimate regression models of the following form:

Execution $\text{cost}_{i,d,b,t}$= f($\text{REL}_{i,d,t}$, $\text{Trans\_Char}_{i,d,b,t}$, $\text{Insurer\_Char}_{i,t}$, $\text{Bond\_Char}_{b,t}$)

$$+\alpha_t + \pi_b + e_{i,d,b,t} \,, \qquad (2)$$

where the variables are described below and α and π are time and bond fixed effects respectively. When estimating the standard errors, we follow Di Maggio, et al. (2017) and double cluster the errors at the bond and week level.

One focus of this analysis is the estimated sensitivity of execution costs with the variables measuring the relationship between insurer i and dealer d at date t, REL. We consider three relationship measures. The first variable, REL_Dum, is a binary measure of relationship that equals one if life insurer i traded with the dealer d in the previous quarter, and 0 otherwise. The other two relationship measures are based on transaction amount (REL_AmtTr) and number of trades (REL_NumTr), defined as

REL_AmtTr =

$$\frac{\textit{Transaction amount} \text{ by life insurer i to dealer d in the previous calendar qrtr (\$)}}{\textit{Transaction amountby life insurer i in the previous calendar qrtr} \text{ (\$)}}$$

REL_NumTr =

$$\frac{\textit{Number} \text{ of bonds traded by life insurer i to dealer d in the previous calendar qrtr}}{\textit{Number of bonds traded by life insurer in the previous calendar qrtr}}$$

Di Maggio et al. (2017) define relationships similarly.

The other focus of the analysis is whether execution costs are influenced by the size of insurer's dealer network and the size of the insurer's bond portfolio, which proxy for the competition for the insurer's business and the value of maintaining a share of the insurer's trading business. We measure the size of the insurer's dealer network in two ways: (1) the number of dealers used in the past calendar quarter (Num_Dealers), and (2) a dichotomous variable equal to one if the insurer has fewer than five dealers in its network, and zero otherwise (NetWork_LT5). We measure the size of the insurer's bond portfolio by the natural logarithm of the insurer's bond portfolio in million (Log_BondHldgs) and a dichotomous variable (BondHldgs_LTMed) equal to one if the insurer's bond portfolio is below the median value of whole sample of insurers, and zero otherwise.

We include a number of control variables in the regression model, many of which have been shown to be related to bond execution costs in previous studies. The first set of control variables includes *Transaction Characteristic*s. We use a dichotomous variable indicating whether the trade was a buy or a sell trade (Sell_Dum) and the natural logarithm of the trade size in millions (Log_TradeSize).

The *Bond Characteristic* control variables are as follows: the natural logarithm of the number of months until maturity (Bond_Maturity), the natural logarithm of the number of months since bond was issued (Bond_Age), the Amihud liquidity measure for the bond (Bond_Liq),[49] the bond's average credit rating during the quarter, with 10 indicating AAA and 1 indicating default (Bond_Rating), a dichotomous variable indicating whether the bond was upgraded (Bond_Upgrade) or downgraded (Bond_Downgrade) in the quarter.

The third set of control variables includes *Insurer Characteristics*: the natural logarithm of the insurer's bond holdings (Log_BondHldgs), the natural logarithm of the insurer's risk-based capital ratio (Log_RBC) ratio, a dichotomous variable equal to one if the RBC ratio is less than five and zero otherwise (RBC_LT5), the insurer's ratio of cash to total assets (Cash_Assets), a dichotomous variable equal to 1 if the insurer is a mutual company and zero otherwise (Mutual), the insurer's return on assets (ROA), a dichotomous

[49] We use a slight variant of the traditional Amihud liquidity measure. In particular, we calculate the median rate of return divided by volume of all of the trades in a quarter. We use the median as opposed to the mean to reduce the impact of outliers. If the value of the liquidity measure is high, then it implies that a trade moves the price more for a given size trade, indicating higher illiquidity or lower market depth (Kyle, 1985).

variable indicating whether the insurer is part of a group that has been designated as a systemically important financial institution (SIFI), dichotomous variables indicating whether the insurer has at least 75 percent of its business from annuities (Annuity_Focus), or 75 percent from life insurance (Life_Focus), or 75 percent from accident and health insurance (A&H_Focus). The dichotomous variable OutsRel is equal to one if the insurer outsourced some of its investment management to an affiliate of the dealer and zero otherwise.[50]

We present descriptive statistics for the variables used in the analysis in Table 4.2. Variable descriptions are collected in the Appendix. The mean and standard deviation of execution costs equal 0.50 and 1.40, respectively, which correspond to 50 and 140 basis points. The mean of the variable REL_Dum indicates that 50.8 percent of the transactions are between an insurer and dealer who traded with each other in the previous quarter. The descriptive statistics for REL_AmtTR and REL_NumTr indicate that across all of the transactions, on average, 12.8 percent of an insurer's trading volume and 12.7 percent of an insurer's trades in the previous quarter went through the same dealer. Note, however, that about half of the transactions are not with a dealer that the insurer used in the previous quarter and thus roughly half of the values for REL_AmtTr and REL_NumTr are equal to zero. For transactions with a previous transaction relationship (i.e., REL_Dum equals one), the mean values of REL_AmtTr and REL_NumTr are both equal to 25.1 percent. The

[50] The outsourcing data is hand collected from "GENERAL INTERROGATORIES" in insurers' annual statements. Life insurers report each advisor's name and address. We then match the name of the outsourcing institutions with the vendor's name in the transaction data. In addition, we use the name and address data to see whether these two advisors are in the same group. We also use SEC affiliated company reports, Bloomberg private company information, and bank regulatory reports to confirm the affiliations.

OutsRel variable indicates that about three percent of trades are made with dealers that also have an affiliate that has an outsourcing relationship with the life insurer.

The average trade size is about $3 million, but the median trade size is about $1.2 million. Bond average maturity is about 8.9 years, and average bond age is 3.9 years. Average bond rating is BBB. In our sample, about 2.5 percent of trades are made in the same quarter as when an upgrade event occurs, and about 9.1 percent of trades are made when a downgrade event happens. From Panel A and Panel B, we can see that the average life insurer size is $18.9 billion when using all trades and $16.5 billion when using insurer-year observations. The difference indicates that life insurers with greater assets make more trades during the same period. Similarly, the average number of dealers based on transactions is 15, but the average number of dealers based on insurer-year observations is five, which indicates that life insurers with a broader dealer network trade more often. Overall, summary statistics show that life insurers with greater bargaining power, as measured by dealer network size and the size of insurer bond holdings, trade more.

4.4.3 Results for the Baseline Model

The results of estimating the baseline model are reported in Table 4.3 for all transactions and separately for buy and sale transactions. To quantify the relationship strength, the models in Table 4.3 use either the variable based on the volume of trading in the prior quarter (REL_AmtTr), based on the number of trades in the prior quarter (REL_NumTr), or the dichotomous variable indicating a relationship trade (REL_Dummy). The correlations between REL_AmtTr, REL_NumTr, and REL_Dummy are 0.94, 0.53 and 0.56. The high correlation suggests that all of our primary relationship variables capture similar phenomena. We view REL_AmtTr as the best measure of the strength of a relationship because it gives the proportion of the insurer's prior quarter trading volume that went to the dealer.

Regardless of which relationship measure is used, the coefficient on the relationship variable is positive and significant at the 1 percent or 5 percent level, except for the coefficient on REL_Dum in the equation for sales. Thus, a stronger prior trading relationship is associated with higher execution costs, on average. However, the positive estimated relation between execution costs and the relationship variables contrasts with the finding of Di Maggio et al. (2017), who show that stronger relationships in dealer to dealer trades, all else equal, lower execution costs. In Di Maggio et al. (2017), they divide the relationship variable into "Fraction Selling to Counterparty" (Fraction Sales/Total Sales) and "Fraction Buying to Counterparty" (Fraction Purchases/Total Purchases). If we follow their definition and re-estimate the table 4.3, the coefficient on "Fraction Buying to Counterparty" is 0.16 and significant at the 1 percent level. The coefficients on "Fraction Selling to Counterparty" is -0.02 but not significant at the 10 percent level. Thus, our results indicate that a stronger prior trading relationship increases execution costs on average. Sharpe (1990) reports an analogous result in banking, i.e., banks charge higher prices to customers with whom they have stronger relationships.

One possible explanation for the different results is that our samples differ. In our insurer transaction data, junk bonds account for about 29 percent and the average transaction volume per trade is about $3.03 million. In Di Maggio et al. (2017), the proportion of junk bonds is less than 10 percent and the average transaction volume per trade is about $4.75 million. Although the different samples could explain the different results, our key point is that the interaction of relationship with other factors is also part of the explanation. In other words, we show below that relationships decrease execution costs in our sample for some transactions, but not others. Our contribution is the identification of the characteristics of transactions that interact with relationships to determine execution costs.

The results in Table 4.3 indicate that the coefficient on Num_Dealers is -0.01 and is statistically significant, indicating that insurers that use more dealers in the past year have lower execution costs on average, all else equal. This is consistent with insurers that possess a more legitimate threat to move their trading business to another dealer obtaining lower execution costs, all else equal. The coefficient estimate suggests that each additional dealer in the network lowers execution costs on average by one basis point, all else equal. A similar result is reported by Hendershott et al. (2015) and O'Hara et al. (2016).

The coefficient on the variable measuring the size of the insurer's bond holdings (Log_BondHldgs) is negative and statistically significant for buy transactions and overall, but not statistically significant for sale transactions. This finding is consistent with execution costs varying based on the value of the relationship to the dealer (Bernhardt et al., 2005). O'Hara et al. (2016) also find that insurers with larger bond portfolios (which they refer to as "more active") have lower execution costs on average.

We now briefly mention some of the results for the control variables, most of which are consistent with other papers. One exception is that we find that execution costs are on average higher for sale trades, in contrast to Hendershott et al. (2015). Table 4.3 indicates that larger orders are associated with lower transaction costs. Bonds that are older, with longer maturity, worse credit rating, or have a downgrade event in the quarter are related to higher bond execution costs. Life insurers with lower RBC ratios, all else equal, pay higher bond execution costs. Finally, mutual insurers on average have higher execution costs, all else equal, although the effect is not statistically significant for sale transactions. One explanation is that mutual insurers could have greater agency problems (see Mayers and Smith, 1981, 1986, 1988) and consequently mutual insurer managers have less incentive to seek better execution costs.

In an unreported table, as robustness checks, we estimate the models presented in Table 4.3, but replace the variable measuring the number of dealers with a dichotomous variable, NetWork_LT5, that takes a value of one if the number of dealers is less than five, and zero otherwise (the median number of dealers is four). In addition, we use an alternative measure of the insurer's bond holdings, a dichotomous variable BondHldgs_LTMed, which equals one if the insurer's bond holdings are less than the median for the sample, and zero otherwise. We do not report these results because the results are consistent with those in Table 4.3 for each variable. The coefficient on the NetWork_LT5 indicates that on average execution costs are higher by between 21 and 28 basis points for insurers with dealer networks consisting of less than five dealers relative to insurers with larger networks. Finally, the coefficient on the BondHldgs_LTMed indicates that on average execution costs are higher by between 8 and 22 basis points for insurers with bond holdings less than median.

In sum, the empirical evidence strongly suggests that relationships are important for explaining the bond execution costs. In addition, life insurers with a broader network and greater bond holdings enjoy lower bond execution costs, all else equal.

4.4.4 The Effect of Customer Market and Relationships on Execution Costs

We now examine whether the impact of relationships depends on the customer's market power, where life insurers with strong market power obtain better prices because the cost to the dealer of losing the insurer's current and future business is higher (Bernhardt et al., 2005, Rhodes-Kropf, 2005). In contrast, if life insurers have weak market power and strong trading relationships (i.e., concentrate their trades with a small set of counterparties), they are likely to pay higher bond execution costs (Sharpe 1990; Rajan 1992). We use two variables to proxy for a life insurer's market power - the number of dealers used by the insurer in the prior year (Num_Dealers) and the value of the insurer's bond holdings (Log_BondHldgs) (Hendershott et al, 2015; O'Hara et al, 2016).

4.4.4.1 Number of Dealers Interacted with Prior Trading Relationship Strength

Hendershott et al. (2015) document the large variation across insurers in the extent to which they trade and with the number of dealers used. For example, they state that 50 percent of insurers trade with only one dealer all of the time. Insurers that only use a few dealers are unlikely to obtain the best execution costs. However, these insurers are also likely to have high relationship strength measures with at least one of their dealers. Thus, the positive relationship between execution costs and strong dealer relationships could be explained by a large number of insurers that only deal with a few dealers. To test whether the impact of relationships on execution costs depends on the number of dealers used by an insurer, we include an interaction term between REL_AmtTr and either the number of dealers (Num_Dealers). This explanation would be supported by the data if the estimated coefficient on the interaction term is negative; indicating that the benefit (lower execution costs) of a stronger relationship increases with the size of the insurer counterparty network.

The results, which are reported in Column 1 of Table 4.4, indicate that the coefficient on the REL_AmtTr variable is positive and statistically significant, as it is in Table 4.3. However, the coefficient on the interaction variable is negative and statistically significant, indicating that the sensitivity of execution costs to the relationship strength variable declines as the number of dealers increases. Given the coefficient estimates, the slope turns from positive to negative when the number of dealers equals 20.

Our interpretation is as follows: On average, when an insurer does not have a large network of dealers, a higher value for relationship strength increases execution costs, but when an insurer does have a large network of dealers, a higher value of relationship strength decreases execution costs. The predicted impact of relationship strength on execution costs for different values for the Num_Dealers is illustrated in Figure 1. As relationship strength increases, predicted execution costs increase as relationship strength increases when the number of dealers is less than 20, but execution costs decrease as relationship strength increases when the number of dealers is greater than 20.

We also estimate the model interacting the dichotomous variable Network_LT5 with REL_AmtTr, but do not tabulate the results. Consistent with the previous discussion, the coefficient on the interaction term is positive and statistically significant, indicating that the estimated slope of the function relating execution costs to REL_AmtTr is greater when the insurer has fewer dealers in its network.

4.4.4.2 Bond Portfolio Size Interacted with Prior Trading Relationship Strength

The model in column 2 of Table 4.4 interacts REL_AmtTr with the size of the insurer's bond holdings. The coefficient on the REL_AmtTr is positive and statistically significant and the coefficient on the interaction term is negative and statistically significant. The coefficient estimates on the REL_AmtTr terms indicate that the slope switches from positive to negative when Log_BondHldgs equals 10, which is a little lower than the mean for the sample. Figure 2 illustrates the predicted impact on execution costs for different values of Log_BondHldgs. Similar results are found if we use the dichotomous variable Bondhldgs_LTMed, instead of Log_BondHldgs.

Columns (3) – (6) in Table 4.4 repeat the estimations present in Columns 1 and 2, except with different fixed effects. They illustrate that the results are robust to including counterparty fixed effects (columns 3 and 4) and including counterparty by month fixed effects (columns 5 and 6). Taken together, the results reported in Table 4.4 provide support for the hypothesis that repeated transactions from the same dealer is associated with a larger reduction in bond execution costs for life insurers with higher market power.

4.5 Effect of Cross Relationships on Execution Costs

We now examine whether execution costs depend on whether the insurer has outsourced some of its asset management to an affiliate of the counterparty. To do this, we include the variable OutsRel, which equals one if the insurer has outsourced some of its investment management with an affiliate of the dealer, and zero otherwise.

We also examine whether outsourcing can enhance an insurer's market power that otherwise would have low market power. From the results in the previous section, we know that greater trading relationship strength increases execution costs for insurers with low market power. To examine whether outsourcing counteracts this effect, we add the triple interaction term: OutsRel × REL_AmtTr × WeakMarketPower. The estimated coefficient on this variable gives the marginal effect of outsourcing on the slope of the estimated line between execution costs and prior trading relationship for insurers with weak market power. Consistent with the previous section, we use two measures of weak market power of life insurer in our tests: NetWork_LT5 and BondHldgs_LTMed.

The results are reported in Table 4.5. The specifications in Columns 1 and 3 include OutsRel only as a dummy variable (not interacted with any other variable). In both cases, the coefficient is negative and statistically significant at the 5 percent level. This suggests that on average outsourcing investment management services to an affiliate of the counterparty is associated with lower execution costs.

In columns 2 and 4, we interact OutsRel with the prior trading relationship strength variable, REL_AmtTr, as well as with the interaction of REL_AmtTr with a dichotomous variable indicating low market power: NetWork_LT5 in column 2 and BondHldgs_LTMed in column 4 (giving a triple interaction variable). In columns 2 and 4, the coefficients on OutsRel are again negative and statistically significant at the 5 percent level. The coefficient on OutsRel× REL_AmtTr is positive and significant at the 10% level in column 2, but not statistically significant in column 4. Finally, the coefficient on the triple interaction terms are negative, statistically significant and economically significant. More specifically, the coefficient for OutsRel × REL_AmtTr × NetWork_LT5 is -1.00, indicating that for insurers with a smaller dealer network (weak market power) execution costs increase at a lower rate with the strength of the prior trading relationship if the insurer has an outsourcing relationship with an affiliate of the dealer. The coefficient for OutsRel× REL_AmtTr × BondHldgs_LTMed is -0.69 and significant at 1 percent level. This result also provides evidence that an outsourcing relationship with an affiliate of the dealer helps to lower execution costs for insurers with relatively low bond holdings (weak market power). Thus, the evidence indicates that the benefit of outsourcing is more significant for life insurers with weak market power.

We illustrate the impact of outsourcing on the sensitivity of execution costs to the relationship strength variable in Figure 3 (based on dealer network) and Figure 4 (based on bond holdings). A comparison of the dashed and dotted lines gives the impact of having an outsourcing relation when the insurer has relatively small market power. Execution costs are lower on average and execution costs decrease with increases in REL_AmtTr when the insurer has an outsourcing relation. This suggests that outsourcing of investment services augments the value of a relationship for insurers that otherwise would have little market power in bond trading relationship.

4.6 Endogeneity of Relationship Trades

Life insurer characteristics (such as bond portfolio size) and transaction characteristics (such as the bond being traded and trade size) may influence the decision to use a relationship dealer. Ideally, we would like to run an experiment with pairs of matched firms that are identical in all aspects except the dealer they use to buy or sell bonds. One firm in each pair would trade a bond with a relationship dealer while the other would trade the same bond at the same time with a non-relationship dealer. However, such an experiment is not practical. Instead, we employ the propensity score matching technique used by Drucker and Puri (2005) and Bharath et al. (2011). In our models, the propensity score for using a relationship dealer is a function of the transaction characteristics, bond characteristics, insurer characteristics, and time (quarter) fixed effect. The transaction characteristics include *Sell*_Dum and *Log_TradeSize*. Bond characteristic variables include Bond life, Bond age, Amihud liquidity measure, credit rating, upgrade event, downgrade event and Log_offering amount. *Insurer Characteristics* include bond holding amount, Log_RBC, cash ratio, mutual dummy, ROA, SIFI dummy, business focus dummy and numbers of dealer.

For each trade we estimate a predicted probability of the trade being a relationship trade. We then match each relationship trade with a set of non-relationship trades that have propensity scores similar to that of the relationship trade. We use one-to-one matching without replacement and set the caliper distance equal to 0.01, similar to Bharath et al. (2011). We report our results in Table 4.6 for the mean bond execution cost difference between the relationship trade and the non-relationship trade by using propensity score estimators to match them.

As illustrated in the first two rows of Table 4.6, the results show that the bond execution costs are higher for relationship trades when we examine matches for all transactions and matches for buy transactions. These are consistent with the regression results presented earlier. Row three indicates that relationship trades are not statistically worse than non-relationship trades for sale trades.

We also split our sample to allow for a comparison of trades made by life insurers with weak market power with matched trades by life insurers with stronger market power, where weak market power is measured by whether the insurer's dealer network is less than five and separately by whether the insurer's bond holdings are less than the median. For both measures, the weaker life insurers suffer higher bond execution costs in relationship trades; however, the difference in execution costs is statistically significant only when we measure market power using the insurer's dealer network size.

Finally, we examine the impact of outsourcing investment management to an affiliate of the dealer on execution costs. The number of these cross relationship trades is relatively small and so we report results for those observations that meet are original caliber constraint and when the caliber constraint is removed. In both cases, we find that the average execution costs are lower for weaker life insurers if they outsource their assets and trade with the same dealer, they enjoy lower bond execution costs.

4.7 Summary

The role of trading relationships between customers and dealers has drawn research attention in recent years. Recent empirical evidence indicates that trading relationship decreases bond execution costs. In contrast, we find that trading relationships increases bond execution costs in life insurer transactions, on average. Consistent with the theoretical model of Bernhardt et al. 2005), we hypothesize that the impact of previous trading relationship depends on other factors, most importantly the customer's market power in the relationship. Our evidence indicates that previous trading relationship decreases bond execution costs for life insurers with greater market power, as measured by the number of dealers in the insurer's dealer network and the larger is the size of the insurer's bond portfolio. In addition, the outsourcing activities decreases the bond execution costs for life insurers with weaker market power. Our results therefore add to our understanding of the role of relationships in financial markets.

Table 4.1: Sample Selection

This table describes the procedures we use to select our sample. Our data of corporate bond transaction and outsourcing status are from the National Association of Insurance Commissioners (NAIC). Bond transaction data include detailed information of all corporate bond trades by insurance companies from 2003 to 2011, including the date and transaction amounts, par valued traded, identity of the insurer and the dealer (or counterparty) of the trade, and the direction of the trade (whether the insurance company is buying from the dealer or selling to the dealer). Characteristics of the issue and the issuer of the traded bond are obtained from the Fixed Income Security Database (FISD).

Data Filiters	Nobs
All NAIC dealer-client bond trades for 2003 to 2011	3,611,435
Drop cusip=missing or transaction date= missing or par=0 or missing	3,540,079
After merging with FISD data for bond issue characteristic	1,269,404
After merging with credit rating	1,041,406
Keep corporate bond	857,438
Drop life<=0.5 or age<0.75	528,897
Drop Foreign Currency, par value not equal to 1000, transaction value=0, no maturity date, no amount outstanding	523,968
Drop non-secondary market trade	434,519
Drop no dealer (blank,0, Various…)	341,008
After merging with valid insurer (normal status)	323,041
Merge with TRACE, delete odd prices, at least two trades on the same side per day	100,416
Merge with outsourcing data, drop unrecognized dealers	98,636
Drop life insurers without RBC ratio and asset; Drop bond without liquidity measure	92,952

Table 4.2: Summary Statistics

Panel A:
The statistics are based on 92,952 bond transactions between a life insurer and a dealer from 2003-2011. Variable definitions are in the Appendix B.

	MEAN	STD	P10	P50	P90
Execution_Cost (basis pts)	0.5	1.4	-0.1	0.3	1.6
Sell_Dum	0.581	0.493	0.000	1.000	1.000
Trade_Size (million)	3.031	4.777	0.101	1.233	7.747
REL_Dum	0.508	0.500	0.000	1.000	1.000
REL_AmtTr	0.128	0.237	0.000	0.004	0.387
REL_NumTr	0.127	0.225	0.000	0.030	0.333
OutsRel	0.031	0.172	0.000	0.000	0.000
Bond Maturity (Month)	106.754	96.185	26.867	79.233	299.533
Bond Age (Month)	46.683	33.872	13.633	37.567	92.233
Bond Liq (Qtr)	0.096	0.160	0.001	0.032	0.269
Bond_Rating	7.127	1.321	5.000	7.000	8.667
Bond_Upgrade	0.025	0.156	0.000	0.000	0.000
Bond_Downgrade	0.091	0.287	0.000	0.000	0.000
RBC	10.568	24.099	5.015	7.769	13.515
BondHldgs(Billion)	14.473	25.296	0.122	3.739	42.752
BondHldgs_LTMed	0.090	0.285	0.000	0.000	0.000
Num_Dealers	15.615	7.807	4.000	16.000	26.000
NetWork_LT5	0.128	0.334	0.000	0.000	1.000
Cash_Assets	0.044	0.066	0.004	0.024	0.098
ROA	0.023	0.060	-0.007	0.012	0.067
Mutual	0.108	0.311	0.000	0.000	1.000
A&H_Focus	0.164	0.370	0.000	0.000	1.000
Life_Focus	0.157	0.364	0.000	0.000	1.000
Annuity_Focus	0.295	0.456	0.000	0.000	1.000
SIFI	0.144	0.351	0.000	0.000	1.000

Panel B: By Life Insurer

The statistics are based on 4,832 life insurers from 2003-2011.

	MEAN	STD	P10	P50	P90
Assets (Billion)	5.697	18.686	0.022	0.525	12.043
BondHldgs(million)	3.889	12.357	0.013	0.369	8.142
BondHldgs_LTMed	0.315	0.464	0.000	0.000	1.000
Num_Dealers	6.963	6.471	1.000	4.000	17.000
NetWork_LT5	0.553	0.497	0.000	1.000	1.000
Cash_Asset	0.065	0.094	0.005	0.032	0.166
ROA	0.027	0.074	-0.016	0.015	0.083
RBC	16.066	53.558	4.472	8.592	25.035
Mutual	0.091	0.288	0.000	0.000	0.000
A&H_Focus	0.228	0.420	0.000	0.000	1.000
Life_Focus	0.283	0.451	0.000	0.000	1.000
Annuity_Focus	0.172	0.378	0.000	0.000	1.000
SIFI	0.053	0.224	0.000	0.000	0.000

Table 4.3: Execution Cost and Previous Transaction Relationship

This table reports the regression coefficient estimates where the dependent variable is execution costs and the explanatory variables are REL_Dum = 1 if there is a transaction relationship with the dealer in the previous quarter and 0 otherwise, REL_AmtTr = ratio of the dollar value of transactions with the dealer to the total dollar value of transactions in the previous quarter, REL_NumTr = ratio of number of deals with the dealer t in Appendix B. We also add week and bond fixed effects. Robust standard errors, double clustered at both the bond and the week levels, are reported in parenthesis. The sample includes bond transactions by life insurers for the period 2003-2011. The dependent variable measured as a percentage of the benchmark price (0.01 is equivalent to 1 basis point; 1.00 is equivalent to 100 basis points). T-values are in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	REL_AmtTr	REL_NumTr	REL_Dum	REL_AmtTr	REL_NumTr	REL_Dum	REL_AmtTr	REL_NumTr	REL_Dum
Observation	All	All	All	Buys	Buys	Buys	Sales	Sales	Sales
REL	0.0013***	0.0014***	0.0004***	0.0015***	0.0014***	0.0005***	0.0010**	0.0012***	0.0003
	(4.5328)	(4.3439)	(3.3207)	(3.8594)	(3.0207)	(2.6424)	(2.2715)	(2.6467)	(1.5744)
Num_Dealers	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(-7.7311)	(-7.5966)	(-8.2723)	(-4.3482)	(-4.2604)	(-5.0672)	(-6.5356)	(-6.4273)	(-6.5983)
Log_BondHldgs	-0.0001*	-0.0001*	-0.0001**	-0.0003***	-0.0003***	-0.0003***	0.0001	0.0001	0.0001
	(-1.8845)	(-1.9533)	(-2.1158)	(-3.7061)	(-3.7570)	(-3.9116)	(1.3457)	(1.3142)	(1.2420)
Sell_Dum	0.0017***	0.0017***	0.0016***						
	(8.6542)	(8.6516)	(8.6356)						
Log_TradeSize	-0.0002***	-0.0002***	-0.0002***	-0.0001	-0.0001	-0.0001	-0.0003***	-0.0003***	-0.0003***
	(-4.1578)	(-4.0617)	(-4.1595)	(-1.2693)	(-1.2084)	(-1.3108)	(-4.6586)	(-4.5815)	(-4.6541)
Bond_Maturity	0.0011***	0.0011***	0.0011***	0.0005	0.0005	0.0005	0.0013**	0.0013**	0.0013**
	(2.7727)	(2.7690)	(2.8005)	(0.6709)	(0.6731)	(0.6754)	(2.2413)	(2.2371)	(2.2559)
Bond_Age	0.0011***	0.0011***	0.0011***	0.0010**	0.0010**	0.0010**	0.0008*	0.0008*	0.0008*
	(3.6242)	(3.6182)	(3.6273)	(2.0920)	(2.0839)	(2.0753)	(1.6710)	(1.6696)	(1.6848)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	REL_AmtTr	REL_NumTr	REL_Dum	REL_AmtTr	REL_NumTr	REL_Dum	REL_AmtTr	REL_NumTr	REL_Dum
Observation	All	All	All	Buys	Buys	Buys	Sales	Sales	Sales
Bond_Liq	0.0080***	0.0080***	0.0080***	0.0064***	0.0064***	0.0064***	0.0109***	0.0109***	0.0109***
	(7.0573)	(7.0624)	(7.0596)	(4.3247)	(4.3295)	(4.3176)	(6.6905)	(6.6876)	(6.6930)
Bond_Ratimg	-0.0011***	-0.0011***	-0.0011***	-0.0014***	-0.0014***	-0.0014***	-0.0011***	-0.0011***	-0.0011***
	(-3.9052)	(-3.9029)	(-3.8741)	(-4.1093)	(-4.1096)	(-4.0807)	(-2.7828)	(-2.7830)	(-2.7682)
Bond_Upgrade	0.0002	0.0002	0.0002	0.0004	0.0004	0.0004	0.0005	0.0005	0.0005
	(0.6205)	(0.6257)	(0.5936)	(0.7770)	(0.7836)	(0.7712)	(0.7796)	(0.7855)	(0.7577)
Bond_Downgrade	0.0013***	0.0013***	0.0013***	0.0024***	0.0024***	0.0024***	0.0007*	0.0007*	0.0007*
	(3.8588)	(3.8624)	(3.8620)	(3.7022)	(3.7149)	(3.7161)	(1.7435)	(1.7436)	(1.7418)
Log_RBC	-0.0003**	-0.0003**	-0.0003**	0.0001	0.0001	0.0001	-0.0006***	-0.0006***	-0.0006***
	(-2.4270)	(-2.3970)	(-2.5529)	(0.4423)	(0.4375)	(0.3906)	(-3.1689)	(-3.1285)	(-3.2440)
Cash_Asset	-0.0002	-0.0002	-0.0001	-0.0018	-0.0019	-0.0019	0.0014	0.0013	0.0014
	(-0.1517)	(-0.1707)	(-0.1451)	(-1.3015)	(-1.3113)	(-1.3633)	(0.8789)	(0.8541)	(0.9083)
ROA	-0.0008	-0.0008	-0.0006	-0.0016	-0.0015	-0.0013	0.0007	0.0006	0.0008
	(-0.7022)	(-0.7177)	(-0.5525)	(-1.3141)	(-1.2909)	(-1.0977)	(0.3672)	(0.3549)	(0.4182)
Mutual	0.0004**	0.0004**	0.0004**	0.0007***	0.0007***	0.0007**	0.0002	0.0002	0.0002
	(2.4667)	(2.4904)	(2.4508)	(2.6159)	(2.6204)	(2.5714)	(0.6934)	(0.7093)	(0.6915)
A&H_Focus	-0.0004**	-0.0004**	-0.0004**	-0.0006*	-0.0006*	-0.0006*	-0.0003	-0.0003	-0.0003
	(-2.2555)	(-2.2327)	(-2.2802)	(-1.8686)	(-1.8692)	(-1.8865)	(-1.2834)	(-1.2611)	(-1.2901)
Life_Focus	-0.0001	-0.0001	-0.0001	-0.0002	-0.0002	-0.0002	0.0001	0.0001	0.0000
	(-0.5227)	(-0.4787)	(-0.6158)	(-0.8180)	(-0.8183)	(-0.9286)	(0.2449)	(0.2759)	(0.2140)
Annuity_Focus	0.0002	0.0002	0.0002	-0.0000	0.0000	-0.0000	0.0004**	0.0004**	0.0004**
	(1.2527)	(1.3061)	(1.2354)	(-0.0318)	(0.0013)	(-0.0719)	(2.0778)	(2.0989)	(2.0759)
SIFI	0.0000	0.0000	0.0000	0.0009***	0.0009***	0.0009***	-0.0005	-0.0005	-0.0005
	(0.1724)	(0.1861)	(0.1825)	(2.7719)	(2.7710)	(2.7507)	(-1.5320)	(-1.5180)	(-1.5232)
Observations	91,261	91,261	91,261	37,227	37,227	37,227	52,159	52,159	52,159

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	REL_AmtTr	REL_NumTr	REL_Dum	REL_AmtTr	REL_NumTr	REL_Dum	REL_AmtTr	REL_NumTr	REL_Dum
Observation	All	All	All	Buys	Buys	Buys	Sales	Sales	Sales
R-squared	0.2208	0.2208	0.2206	0.2613	0.2612	0.2610	0.2930	0.2931	0.2929

Table 4.4: Execution Cost and The Interaction of a Previous Transaction Relationship with Customer Market Power

This table reports the regression coefficient estimates where the dependent variable is execution costs and the explanatory variables are AmtTr = ratio of the dollar value of transactions with the dealer to the total dollar value of transactions in the previous quarter and various measures of Customer Market Power and interactions of Rel_Amt Tr with the customer market power variables. Bond and insurer control variable included in the models reported in Table 3 are also included in these models, but the coefficients are not reported. We also add week and bond fixed effects. Robust standard errors, double clustered at both the bond and the week levels, are reported in parenthesis. The sample includes bond transactions by life insurers for the period 2003-2011. The dependent variable measured as a percentage of the benchmark price (0.01 is equivalent to 1 basis point; 1.00 is equivalent to 100 basis points). T-values are in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

VARIABLES	(1) markup	(2) markup	(3) markup	(4) markup	(5) markup	(6) markup
Rel_Amt_Tr	0.20***	0.30***	0.20***	0.27***	0.22***	0.29***
	(4.16)	(4.07)	(3.55)	(3.85)	(4.01)	(4.14)
Num_Dealers	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(-6.53)	(-7.60)	(-6.89)	(-7.40)	(-7.01)	(-7.71)
Log_BondHldgs	-0.01*	-0.01	0.00	0.00	-0.00	0.00
	(-1.84)	(-1.17)	(0.12)	(0.68)	(-0.05)	(0.63)
Rel_Amt_Tr X Num_Dealers	-0.01**		-0.01**		-0.01***	
	(-2.26)		(-2.17)		(-2.76)	
Rel_Amt_Tr X Log_BondHldgs		-0.03**		-0.02**		-0.03***
		(-2.49)		(-2.42)		(-2.88)
Observations	91,261	91,261	91,130	91,130	90,408	90,408
R-squared	0.22	0.22	0.25	0.25	0.29	0.29
<u>Fixed Effects</u>						
Week and cusip	Yes	Yes	Yes	Yes	Yes	Yes
Counterparty	No	No	Yes	Yes	No	No
Counterparty X month	No	No	No	No	Yes	Yes

Table 4.5 Execution Cost and Cross Relationships

This table reports the regression coefficient estimates where the dependent variable is execution costs and the explanatory variables are AmtTr = ratio of the dollar value of transactions with the dealer to the total dollar value of transactions in the previous quarter and outsourcing activity and interactions of Rel_Amt Tr with the customer market power variables. Bond and insurer control variable included in the models reported in Table 4.3 are also included in these models, but the coefficients are not reported. We also add week and bond fixed effects. Robust standard errors, double clustered at both the bond and the week levels, are reported in parenthesis. The sample includes bond transactions by life insurers for the period 2003-2011. Asterisks denote significance levels (***=1%, **=5%, *=10%).

	Execution Costs (1)	Execution Costs (2)	Execution Costs (3)	Execution Costs (4)
REL_AmtTr	0.04	0.01	0.08**	0.06*
	(1.29)	(0.48)	(2.56)	(1.86)
NewWork_LT5	0.17***	0.16***	0.20***	0.20***
	(7.46)	(6.83)	(9.08)	(8.88)
BondHldgs_LTMed	0.15***	0.15***	0.12***	0.12***
	(5.84)	(5.90)	(4.46)	(4.07)
REL_AmtTr * NetWork_LT5	0.15**	0.22***		
	(2.43)	(3.30)		
REL_AmtTr * Bondhldgs_LTMed			0.11*	0.20***
			(1.71)	(2.86)
OutsRel	-0.13**	-0.21**	-0.13**	-0.18**
	(-2.43)	(-2.22)	(-2.37)	(-2.32)
REL_AmtTr * OutsRel		0.73*		0.28
		(1.83)		(1.50)
NetWork_LT5*OutsRel		0.20		
		(1.56)		
REL_AmtTr * Network_LT5 *OutsRel		-1.00**		
		(-2.36)		
Bondhldgs_LTMed*OutsRel				0.23*
				(1.74)
REL_AmtTr * Bondhldgs_LTMed*OutsRel				-0.69***
				(-2.84)
Other Control Variables	Yes	Yes	Yes	Yes
Cusip Fixed Effects	Yes	Yes	Yes	Yes
Week Fixed Effects	Yes	Yes	Yes	Yes
Observations	91,261	91,261	91,261	91,296
R-squared	0.2209	0.2209	0.2219	0.2218

Table 4.6 Propensity Score Matching Estimation

This table provides estimates of the mean difference between the execution costs of matched relationship trades and non-relationship trades. For the estimation of the propensity score, we use Probit regressions in which the dependent variable is REL, which takes the value of 1 if the insurer has previous trading relationship with the dealer, 0 otherwise. The propensity score for using a relationship dealer is a function of the transaction characteristics, bond characteristics, insurer characteristics, and time (quarter) fixed effect. The dependent variable measured as a percentage of the benchmark price (0.01 is equivalent to 1 basis point; 1.00 is equivalent to 100 basis points). T-values in brackets. $*$, $**$, or $***$ means the coefficient is significant at the 10%, 5%, or 1% level, respectively.

	Observation	Mean Difference in Execution Costs for Relationship vs. Non Relationship Trade	T-Value	Group Difference
Full Sample	31,990	0.0002**	-2.13	
Buys	18,391	0.0005***	-3.11	
Sales	13,373	-0.0000	-0.32	
NetWork_LST=1	3,016	0.0008*	-1.79	
NetWork_LT5=0	27,862	0.0001	-0.91	0.0007*
BondHldgs_LTMed=1	2,395	0.0006	-1.25	
BondHldgs_LTMed=0	29,025	0.0001	-0.68	0.0005
NetWork_LT5=1 & OutsRel=1	304	-0.0031**	2.05	
NetWork_LT5=1 & OutsRel=0	2,473	0.0017***	3.59	-0.0048***
BondHldgs_LTMed =1 *&* OutsRel=1	120	-0.0014	0.64	
BondHldgs_LTMed =1 *&* OutsRel=0	2,100	0.0011**	2.23	-0.0025
NetWork_LS5=1 & OutsRel=1 (Release caliper distance constraint)	452	-0.0025**	-1.98	
NetWork_LS5=1 & OutsRel=0 (Release caliper distance constraint)	2,892	0.0018***	4.05	-0.0043***
BondHldgsLsMed =1*&* OutsRel=1 (Release caliper distance constraint)	229	-0.0022*	-1.66	
BondHldgsLsMed =1*&* OutsRel=0 (Release caliper distance constraint)	2,175	0.0015***	3.01	-0.0037**

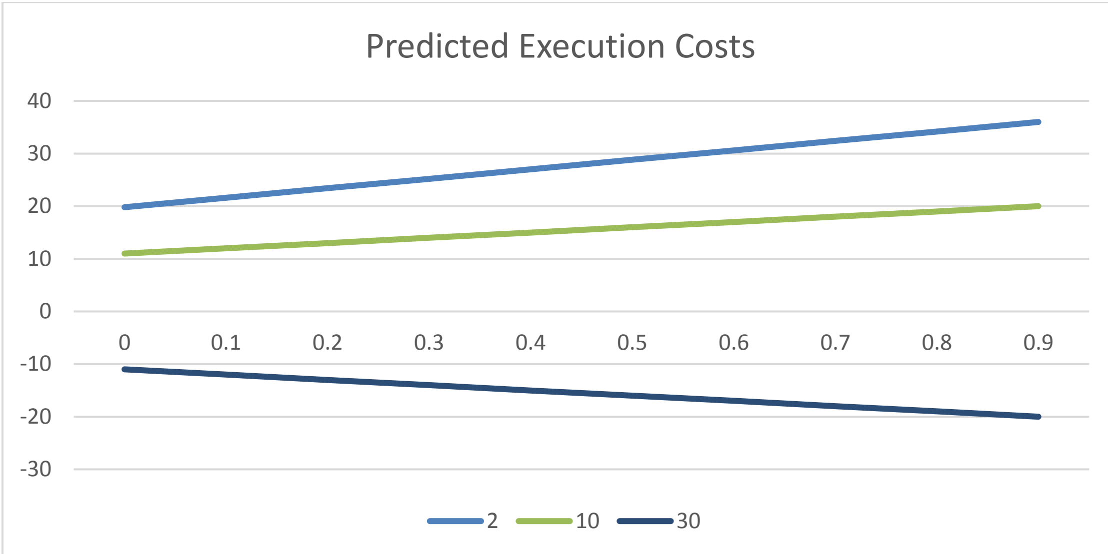

Figure 4.1 Predicted Execution Costs (in basis points) as a function of REL_AmtTr when the Num_Dealers equals 2, 10, and 30 relative to the predicted execution costs when Num_Dealers = 20

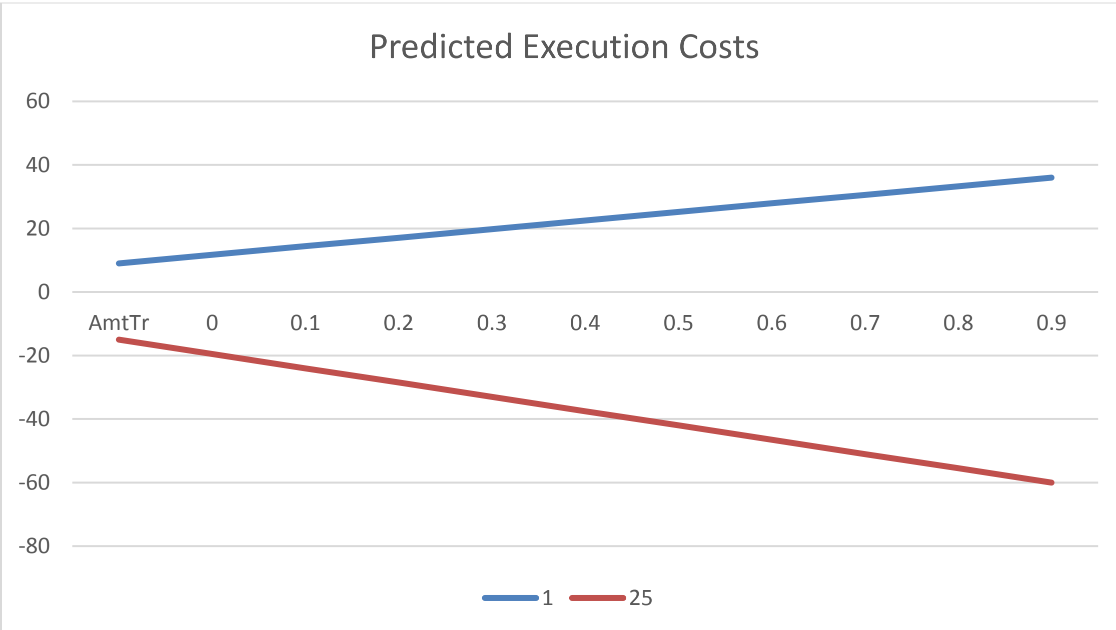

Figure 4.2 : Predicted Execution Costs (in basis points) as a function of REL_AmtTr when the Log_BondHldgs equals 1 and 30 relative to the predicted execution costs when Log_BondHldgs equals 20

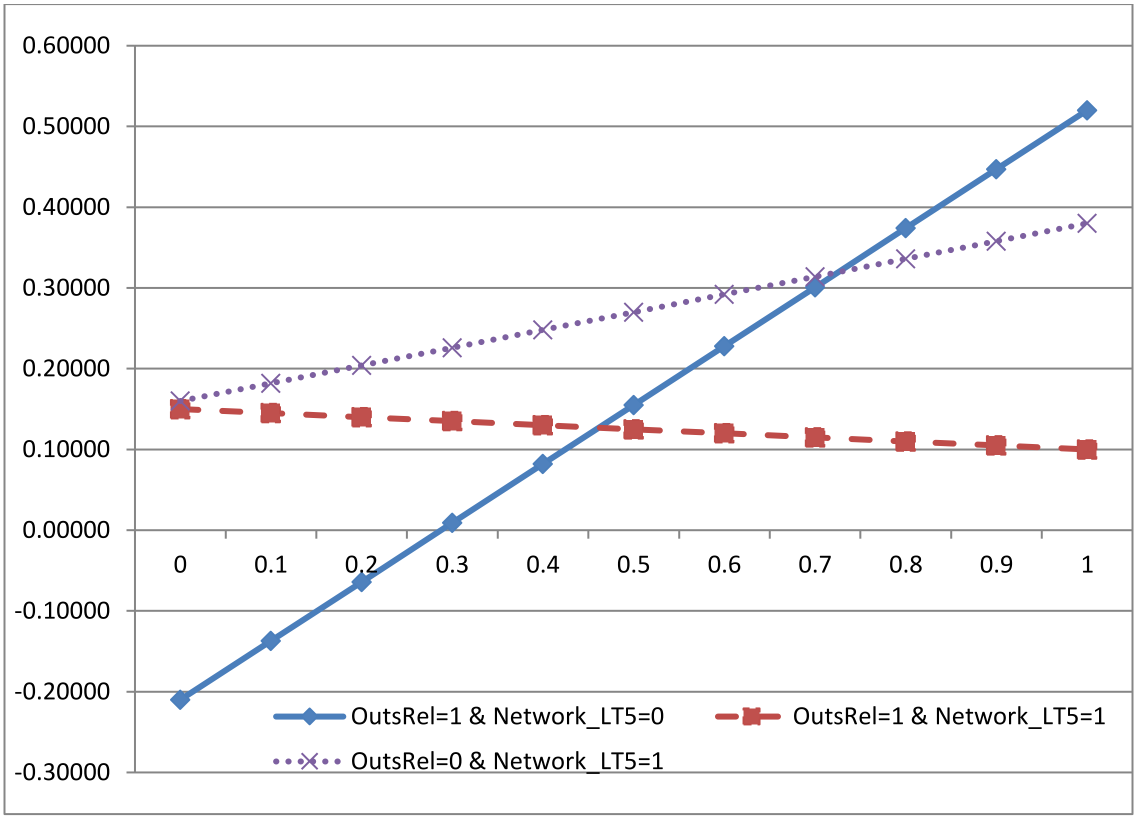

Figure 4.3: Predicted Execution Costs (in basis points) as a function of REL_AmtTr for different values of dealer network size (Network_LT5) and outsourcing (OutsRel).

The predicted execution costs are relative to the predicted execution costs when Network_LT5=0 and OutsRel =0

CHAPTER 5

CONCLUSION

The Gramm-Leach-Bliley Act of 1999 (GLBA) allowed U.S. financial conglomerates to engage in both banking and insurance under one roof, similar to universal banks in Europe (Carow, 2000; Morrison, 2015). However, regulators have remained concerned about the potential negative effects involved in combining banking and insurance, and about the connections between financial institutions more generally. The 2008 financial crisis heighted these concerns, My dissertation contributes to our understanding of how the relationships among financial institutions influence the behavior and performance of individual financial institutions, as well as market level outcomes.

In the first essay, I find that life insurers with bank affiliates experienced higher premium growth than life insurers without bank affiliates, mainly from annuity products. This result is consistent with banks internally transferring deposit customers to the annuity products provided by an affiliated life insurer, which supports the benefits of combining banks and life insurers "under one roof." However, the group performance of organizations with banks and life insurers was worse than what stand-alone banks and life insurers during the same period. Overall, the benefits of transferring customers to affiliated insurers were not large enough to increase the group's performance.

In the second essay, we find that life insurers tend to be on the same side of the market (either buying or selling) in individual corporate bonds. Although correlated trading could be a possible source of systematic risk (see e.g., FSOC (2013), Getmansky et al. (2016) Paulson and Rosen (2016), and Schwarcz and Schwarcz, 2014), we find little evidence that insurer herding caused prices to move away from fundamental values during our sample period. The implications of the results therefore do not support the hypothesis that life insurers are systemically important through their investment behavior.

In the third essay, we find that previous trading relationship decreases bond execution costs for life insurers with greater market power, as measured by the number of dealers in the insurer's dealer network and the larger is the size of the insurer's bond portfolio. In addition, outsourcing of investment management services to an affiliate of a bond dealer decreases the bond execution costs for life insurers with weaker market power. Our results, therefore, add to our understanding of the role of relationships in financial markets.

The findings show that the relationships among financial institutions are complicated. First, affiliations in the same groups may help each other during the financial crisis, but the cross-selling effects were not enough to improve the performance during the crisis. Second, although life insurers' investment decisions are correlated, the correlated trading does not appear to disrupt the bond markets. Finally, the impacts of previous trading relationships are not monotonic. The interaction effects between customer market power and previous trading relationship determine bond execution costs.

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APPENDIX A

LSV MEASURE ILLUSTRATION

To illustrate the LSV measure, suppose that five bonds are in the sample and the deviations of each bond's buy ratio from the overall average buy ratio ($p_{it} - p_t$) equal -0.3, -0.1, 0.1, 0.2, and 0.3. For simplicity, assume the adjustment factor for each security is zero, then the following table would give the herding measures for each of the five bonds and the average herding measures.

The average overall herding measure (LSV_HM) for the sample would be 0.2, the average of the absolute values of the five individual deviations. The average sell herding measure would be 0.2, the average of the absolute values of the two negative deviations; and the average buy herding measure would be 0.2, the average of the three positive deviations.

Table A.1 LSV example

Bond	$p_{it} - p_t$	LSV_HM	LSV_SHM	LSV_BHM
1	-0.3	0.3	0.3	
2	-0.1	0.1	0.1	
3	0.1	0.1		0.1
4	0.2	0.2		0.2
5	0.3	0.3		0.3
Average		0.2	0.2	0.2

APPENDIX B

CHAPTER 4 VARIABLE DESCRIPTIONS

Variable	Description
Execution_Costs	*Execution_Costs is the percentage difference between the price paid on a transaction and the volume weighted average TRACE price for that bond on the same day*
REL_Dum	*REL_Dum* is a measure of relationship strength. *REL_Dum* equals 1 if there is a transaction relationship with the dealer in the previous quarter and 0 otherwise.
REL_AmtTr	*REL_AmtTr* is a measure of relationship strength. It is the ratio of the dollar value of transactions with the dealer to the total dollar value of transactions made by the life insurer in the previous quarter
REL_NumTr	*REL_NumTr* is a measure of relationship strength. It is the ratio of number of deals with the dealer to total number of transactions made by the life insurer in the previous quarter
OutsRel	*OutsRel* equals one if the insurer has outsourced some of its investment management with an affiliate of the dealer, and zero otherwise
Transaction Characteristics	
Sell_Dum	A dummy variable equal to one if the life insurer is selling
Log_TradeSize	the natural log of transaction amount in real year 2003 dollars in million
Bond Characteristics	
Bond_Maturity	Maturity is the natural log of the length in months between transaction date and maturity date.
Bond _Age	The natural logarithm of the number of months since bond was issued
Bond_Liq	The Amihud liquidity measure for the bond
Bond_Rating	Bond i's average rating score during quarter t (1 = AAA, … 10 =default)
Bond_Upgrade	A dummy variable equals 1 if $Rating_{it}$ decreases during quarter t, and 0 otherwise

Bond_Downgrade	A dummy variable equals 1 if $Rating_{it}$ increases during quarter t, and 0 otherwise
Life Insurer Characteristics	
Log_RBC	The natural logarithm of the insurer's risk-based capital ratios
RBC_LT5	Equal to one if the insurer's RBC ratio is less than 5, and zero otherwise.
Log_BondHldgs (in millions)	The natural log of general account asset in million in real year 2003 dollars.
BondHldgs_LTMed	A dichotomous variable, which equals one if the insurer's bond holdings are less than the median for the sample, and zero otherwise.
Num_Dealers	The number of dealers that traded with the life insurer in year t.
NetWork_LT5	A dichotomous variable, which equals one if the number of dealers traded with the life insurer in year t is less than 5, and zero otherwise.
Cash_Assets	The ratio of cash to total asset.
ROA	Average return on assets of insurers transacting in bond i during quarter t,
Mutual	A dummy variable equals 1 if the life insurer is a mutual company, and 0 otherwise.
A&H_Focus	A dichotomous variable that equals 1 if the average percentage of premiums written in accident & health insurance exceeds 75 percent, and zero otherwise.
Life_Focus	A dichotomous variable that equals 1 if an insurer's percentage of premiums written in life insurance exceeds 75 percent, and zero otherwise.
Annuity_Focus	A dichotomous variable that equals 1 if the average percentage of premiums written in annuity exceeds 75 percent, and zero otherwise.
SIFI	Dummy variable equals one if the life insurer belongs to a SIFI during quarter t, and 0 otherwise